MULTI-MISSION SIZING AND SELECTION METHODOLOGY FOR SPACE HABITAT SUBSYSTEMS

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MULTI-MISSION SIZING AND SELECTION METHODOLOGY FOR SPACE HABITAT SUBSYSTEMS

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Earth is the cradle of humanity, but one cannot remain in the cradle forever.

Konstantin Tsiolkovsky

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This thesis could not have been achieved without the help and support of many people. I was lucky enough to be surrounded by a great team who helped me achieve my work.

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SUMMARY

Future space missions aim to set up exploration missions in further space and establish settlements on other celestial bodies like the Moon or Mars. In this context, subsystem sizing and selection is crucial, not only because resource management is critical for the astronauts' survival, but also because subsystems can account for more than 20% of the total mass of the habitat, so reducing their size can greatly impact the cost of the mission.

A few tools already exist to size space habitat subsystems and assess their performance. However, these tools are either very high-fidelity and very slow or instantaneous but steady-state. Steady-state tools do not allow to take risks or mission variations into account and the dynamic, slower tools are less performing at helping stakeholders evaluate the impact of technology trade-offs because of their long running time. Faster sizing tools would also allow to implement additional capabilities, such as multi-mission sizing, which could be used to develop lunar or martian settlements. These tools are also used in the context of point-based design, which focuses on the development of one design throughout the process. Such approach can lead to a sub-optimal design because the selection of an alternative is made early in the design process, based on low-fidelity analyses. In addition, because the costs and design choices are committed early in the design process, requirements or design changes can have very significant cost consequences.

This research proposes a new sizing capability, developed using HabNet [1], a dynamic space habitat simulation tool. It is faster than existing dynamic sizing tools and it allowed to develop a multi-mission sizing methodology using Design Space Exploration. Moreover, leveraging the faster sizing tool developed to create surrogate models for the size of the elements in the habitat, it was shown that trade-off analyses can be used to support set-based design during the conceptual design phase.

Consequently, the methodology proposed is faster than what is currently used to size and select space habitat subsystem technologies. It gives more insight to the user because it can

perform instantaneous trade-offs. However, the quality of the surrogate models generated is not sufficient to validate the multi-mission sizing method and environment developed during this thesis.

This methodology could be used as a basis for the development of a set-based design method for space habitats. Numerous capabilities, including the evaluation of the impact of disruptions or the level of uncertainty associated with the various alternatives considered, could be easily implemented and added to the existing tool.

CHAPTER 1
INTRODUCTION AND MOTIVATION

1.1 Space Exploration Challenges

For centuries, human history has been shaped by attempts to explain the presence of life on Earth through either religious or scientific means. Even today, it is not clear how the Sun and the Earth were formed [2] and how life came to be on our planet. These fundamental questions, which are of both scientific and philosophical interest, are just many among others that space exploration and its associated research aim to tackle.

Space exploration supports several objectives: it addresses hundreds of questions brought by scientific curiosity, it expands human presence into the Solar system, it engages the public for educational purposes, it stimulates economic prosperity and it fosters international cooperation [3]. In particular, space exploration facilitates the development of space-related markets such as space tourism or, in a longer-term perspective, asteroid mining.

To develop space exploration at a global level and to leverage international collaboration in the sector, several countries founded the International Space Exploration Coordination Group (ISECG) initiative. The ISECG intends to drive innovation, knowledge gain, global cooperation and inspire the youth to study science [3]. Thanks to this initiative, significant scientific progress has been made on Earth using knowledge acquired for space exploration. For instance, new technologies have contributed to greatly improve medical robotics, remote medical care for isolated places on Earth, or water purification [3], just to name a few. As part of this initiative, the National Aeronautics and Space Administration (NASA) is now planning to fly astronauts beyond the Moon, with the long-term goal of sending humans to Mars [4], as shown in Figure 1.1. These first Mars explorers would live for some time on the surface of the planet, accomplishing daily exploration and research tasks [5].

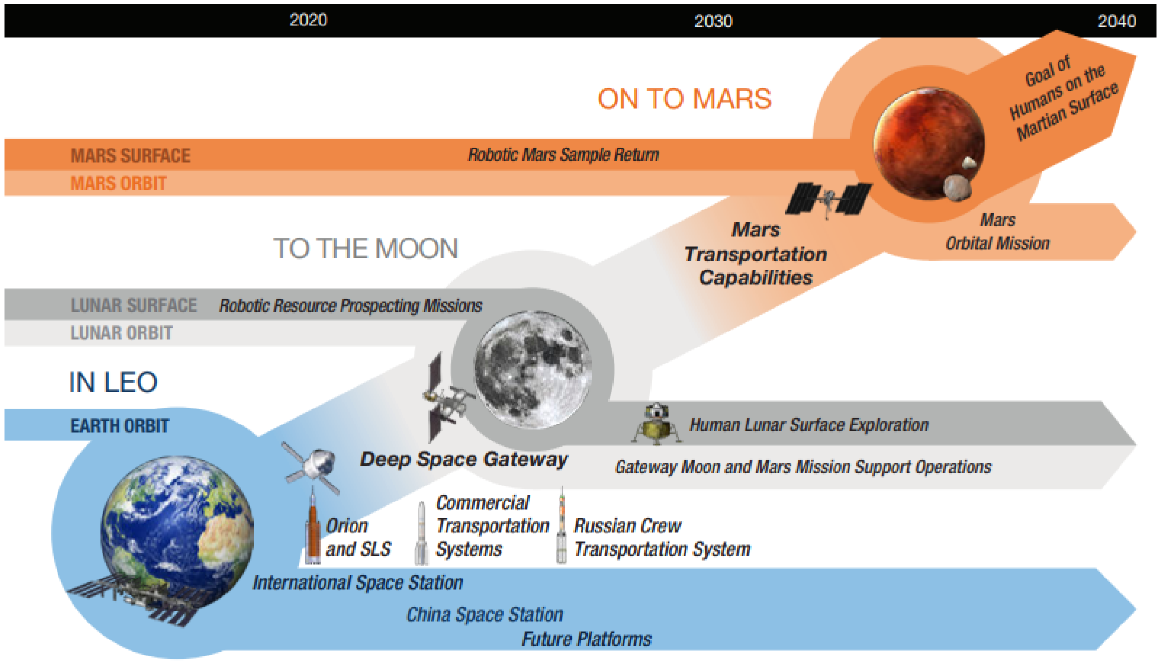

Figure 1.1: NASA's global exploration roadmap [3]

The scientific analysis of the past and current states of the Martian environment, in particular, could help provide insight on the climate change processes on Earth [3]. Sending a crewed mission to Mars is an enormous challenge that will need to build on the knowledge accumulated during past space programs.

1.2 Before Mars, the Moon

Sending humans to Mars is one of NASA's most important long-term goals [3]. To reach its objective, the space agency needs to prepare for two great technical challenges: first, it needs to be able to fly astronauts as far as Mars, and second, it needs to provide them with all the equipment and resources necessary to live on the surface of the Red Planet for several months.

Mission Artemis is a new NASA mission designed to practice sending humans more than 50 million kilometers from the Earth. This new project, previously called "Exploration

Mission" (EM), consists of several steps, all revolving around the development and testing of the capabilities of the Space Launch System (SLS) [6]. Artemis-1 is an unmanned mission scheduled for 2020 that should demonstrate the SLS's ability to go beyond the Moon. Artemis-2 should launch in 2024 and bring humans back to the Moon for the first time since 1972.

To address the second challenge, five of the most important space agencies, NASA, the European Space Agency (ESA), the Russian space agency (Roscosmos), the Japan Aerospace Exploration Agency (JAXA) and the China National Space Administration (CNSA) decided to combine their knowledge and talent to create the Gateway [7]. The Gateway is a spaceship designed to orbit permanently around the Moon, it is planned to be built between 2022 and 2026. Its mission is "to test new tools, instruments and equipment that could be used on Mars, including human habitats, life support systems, and technologies and practices that could help us build self-sustaining outposts away from Earth" [8]. Observing how astronauts react physically and psychologically to living in the Gateway could also bring useful information to researchers. In addition, the spaceship could help support deep space missions if used as a refueling and maintenance station. An illustration of the lunar Gateway is provided in Figure 1.2.

Three agencies, ESA, NASA and CNSA, have also announced their plan to build a permanent settlement on the surface of the Moon [9, 10, 11, 12]. This lunar base would be an international research facility where space agencies and private companies work together. Like the Gateway, it would enable testing of new life support technologies and would be the first space habitat to stand on the surface of a celestial body. An estimated timeline for Moon exploration is presented in Figure 1.3. Based on this schedule, the 2030s should witness the use of the first surface habitats with support systems and In-Situ Resource Utilization (ISRU).

However, before then, a surface habitat needs to be designed, tested and deemed safe to host astronauts on the Moon.

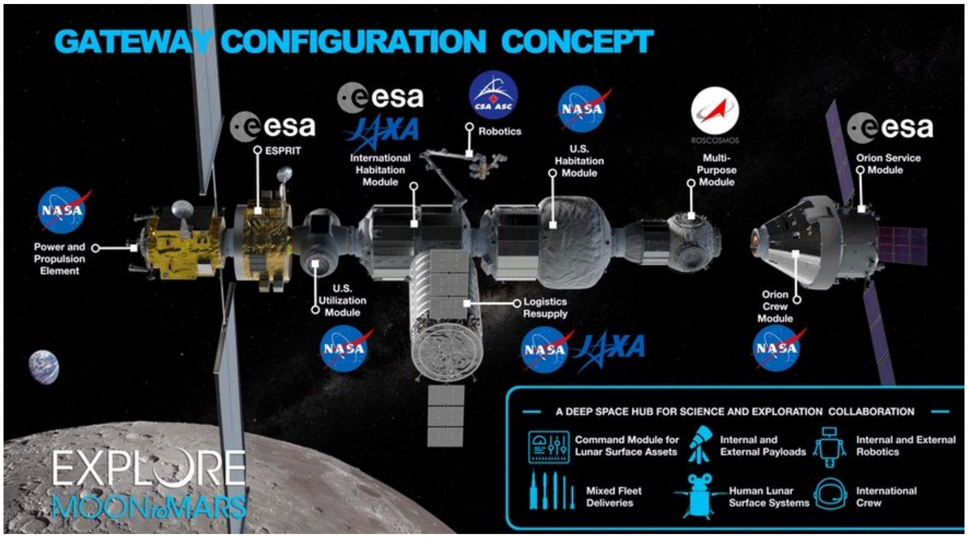

Figure 1.2: Lunar Gateway configuration, according to NASA, as of March 2019 [7]

1.3 A need for space habitats

The Merriam-Webster dictionary defines a habitat as "a housing for a controlled physical environment in which people can live under surrounding inhospitable conditions" [13]. We can extend this definition to space habitats: a space habitat is a shelter for astronauts, containing a controlled environment that meets their physical needs (water, oxygen, food...), in an inhospitable context such as space or the surface of a celestial body. Space habitats can be:

- orbital, like the International Space Station (ISS) or the Gateway; they are often called "space stations"
- located on the surface of a celestial body, as they would probably be for a crewed mission to Mars
- designed for transit, in case of long-distance travel to Mars or beyond.

As mentioned earlier, space habitats will play a critical role in the future settlement of humans on the Moon, and, in a farther future, on Mars. Therefore, there is a real need for space habitats to be designed and sized such as to meet the long-term objectives associated

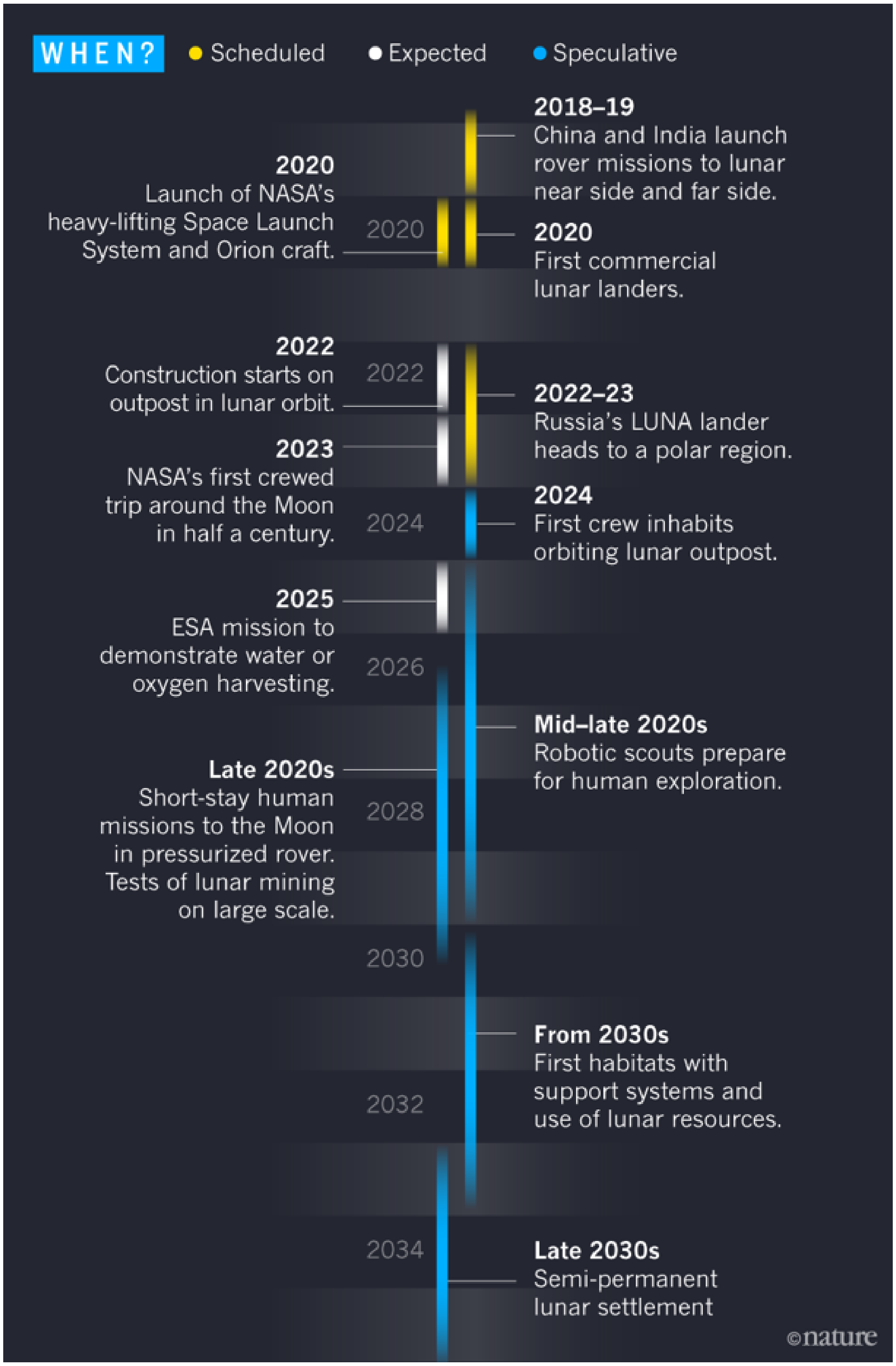

Figure 1.3: Moon exploration timeline, according to [12]

with supporting life in space.

This problem is complex and challenging due to the numerous inherent qualities of space habitats driven by resiliency and sustainability requirements. Indeed, to fulfill their mission, space habitats need to be sustainable, because any resupply would be very expensive and require the utilization of a dedicated spacecraft. They also have to be partially automated, in order to handle the different resources available to the crew. To this end, software and hardware must communicate in the habitat, exchanging information and controlling the habitat parameters. Finally, space habitats need to be resilient and robust to the numerous threats and possible failures that can occur because of radiation, inhospitable environment or interdependencies between different elements of the habitat [14]. Therefore, safety margins, diversity of solutions, redundancy and adaptability are necessary to account for potential disruptions.

Therefore, the overarching research question this thesis aims to address is:

How to design space habitats for the missions they need to support?

To guide the definition of an answer to the overarching question formulated in this chapter, Chapter 2 first provides a literature review of the design methods used for past and present missions. Chapter 3 seeks to identify the technical challenges and gaps in the state of the art, regarding subsystem sizing and integration. Chapter 4 lays out a methodology to address the research problem defined in Chapter 3. Chapters 5 and 6 focus on the steps taken to implement this methodology and compare it to the existing design process. Finally, Chapter 7 discusses the outcomes of this research.

CHAPTER 2
BACKGROUND

This chapter aims to provide a better understanding of the challenges raised by the overarching research question presented in the first chapter. In particular, it describes past and contemporary space habitat design initiatives. The historical design methodology and the associated tools will be presented and their weaknesses will be discussed in the last section of this chapter.

2.1 Space habitat designs

This section discusses the past and current space habitats, which are used to provide design guidelines for the future spacecraft.

2.1.1 Historical space habitats

Several spaceships and space stations have been designed throughout history to shelter astronauts in space. Their design shaped the current and future space habitats. Among them, we can cite the Russian space station Mir (retired) or the ISS, still in activity, which is the most advanced fully developed space habitat to date. An overview of the different habitats and their corresponding mission duration is given in Table 2.1.

Past and current missions enable researchers to better understand the challenges of a long-term presence in space and to identify and test new solutions. To help design teams understanding the requirements associated with crewed space missions, NASA developed human-centered design guidelines [16, 17]. These guidelines use the knowledge collected during the past crewed missions and recommend to actively involve experienced users, like former astronauts. Their feedback is precious to account for all aspects of the mission.
For example, the NASA Space Flight Human-System Standard [17] provides requirements

Table 2.1: Habitats of historical missions, adapted from [15]

Mission	Habitat type	Crewmembers	Mission duration (days) (max/min)
Apollo CM (with LM)	Transit	3 (2)	6d 3h (Apollo 8)
Skylab	Orbital	3	28-84
Salyut	Orbital	3	16-237
Mir	Orbital	2-3 (and visiting crew)	73-438
ISS	Orbital	2-6 (and visiting crew)	215

linked to previous mission observations. One of these requirements states that "the net habitable volume and interior configuration shall support crew behavioral health"[17], based on the observation that confinement, isolation and the stress linked to a space mission usually increase with duration.

In order to develop and test new volumes, configurations and new technologies for space habitats that comply with these guidelines, NASA developed analog missions [18, 19].

2.1.2 Analog missions

Analog missions are field tests conducted in locations physically similar to extreme space environments in order to test new equipment before sending it to space [18]. These tests also allow to study team dynamics and to observe human behavioral changes due to isolation.

The best-known analog mission developed by NASA is the Habitat Demonstration Unit (HDU), built in 2010-2011 (see Figure 2.1). The HDU was created to develop and test different habitat systems and technologies for the ISS and future missions [20]. It is now used by NASA for its Human Research Program (HRP), which started in 2013 [21], to investigate the psychological effects of isolation, light and dark cycles and distance from Earth on the crew, as part of mission Human Exploration Research Analog (HERA) [18].

Human Exploration Spacecraft Testbed for Integration and Advancement (HESTIA) is another analog mission designed to test new Environmental Control and Life Support System (ECLSS) technologies at different pressures [19]. It is also used to test various habitation

Figure 2.1: Picture of the Habitat Demonstration Unit, in 2011 [21]

concepts and to evaluate the effects of elevated carbon dioxide (CO_2) exposure on the human body.

Therefore, not only do these analog missions allow for the development of fully integrated space habitat designs, like the HDU, but they are also a great opportunity to test new technologies and study human behavior. They can be used to create or modify the current requirements for space habitats and help defining the main characteristics of space habitats.

2.2 Characteristics of space habitats

To accomplish their main purpose, which is to protect humans from inhospitable surroundings and help them accomplish their daily activities [14], space habitats must be:

- *Sustainable:* they must produce or recycle all elements necessary to human life during the time of the mission [22, 17, 23]

- *Comfortable:* the crew needs comfort for both functional and psychological reasons [15, 14, 23]

- *Resilient:* space habitats must resist or react quickly when disruptions arise [24]

- *Transportable:* the different parts of a habitat need to be transported to the place where it will be deployed. This aspect can be very cost-intensive [23]

Space habitats are designed and sized to fulfill a mission [14] and its associated requirements.

2.2.1 Mission requirements

The lifecycle of space habitats is divided into four main parts: first, the habitat needs to be transported to the place where it will be installed. In [23], it is mentioned that one of space habitats requirements is that they should be transportable with existing launchers, which means that all parts have size limitations due to the diameter of the available launch vehicles. The launch payload center of gravity is also an important factor, which must be taken into account during the design phase.

Then, the habitat is assembled on-site by human or robotic means [14]. It can be set up all at once or in several steps, as it was done for the ISS [23]. Once the habitat is partially or completely deployed, it is used to support the daily missions of the human crew it accommodates. Eventually, when the habitat becomes obsolete, it can be dismantled or renovated.

As mentioned before, the main purpose of a space habitat is to host and assist the human crew in its daily operations. We can assume that the activities and schedule of the crew would be similar to that of the crew on the ISS [25, 26]:

- 8.5 hours of sleep
- 2 hours of exercise; the length of this activity could vary depending on the length of the mission and the gravity of the planet where it takes place
- Research experiments, chores and routine maintenance of the habitat
- Shared meals
- Briefings
- Hygiene

- Leisure

Each of these activities is linked to requirements that have an impact on resource production or on the configuration of the habitat. To give a few examples, listed in [17], the habitat must provide volume, sleep surface area and personal sleep items for each of the crewmembers. The system must also provide a minimum of 2.0 kg of potable water per crewmember per day for drinking. Potable water is also needed for hygiene and water rations are increased when the crewmembers perform suited operations.

Part of the mission, especially if it is conducted on the surface of a celestial body, would involve Extra-Vehicular Activities (EVAs). EVAs can be planned to carry out research on the spatial environment the habitat is implanted in or to perform outdoor maintenance operations. EVAs are very design-constraining because the robotic vehicles used for exploration need to be fueled. In addition, they increase the need for resources such as oxygen, food and water [17].

2.2.2 Physical breakdown of the habitat

Based on this list of daily activities several functional areas can be outlined [27]: sleeping space, dining and communal areas, work space, exercise (that can be merged with EVA suit donning and medical care), hygiene-dedicated space, translation portals or pass-throughs, and stowage access.

These different areas are represented in the layout of the HDU, as illustrated in Figure 2.2. The first floor is represented on the left of the figure, and the second floor on the right. Under the first floor is the stowage area, and above the second floor are the crew quarters.

This physical breakdown of the space habitat allows us to better understand the different spaces that need to be built into it. Some of these areas can be merged [15] to limit the total volume and surface of the habitat, which makes it more easily transportable and consequently reduces costs.

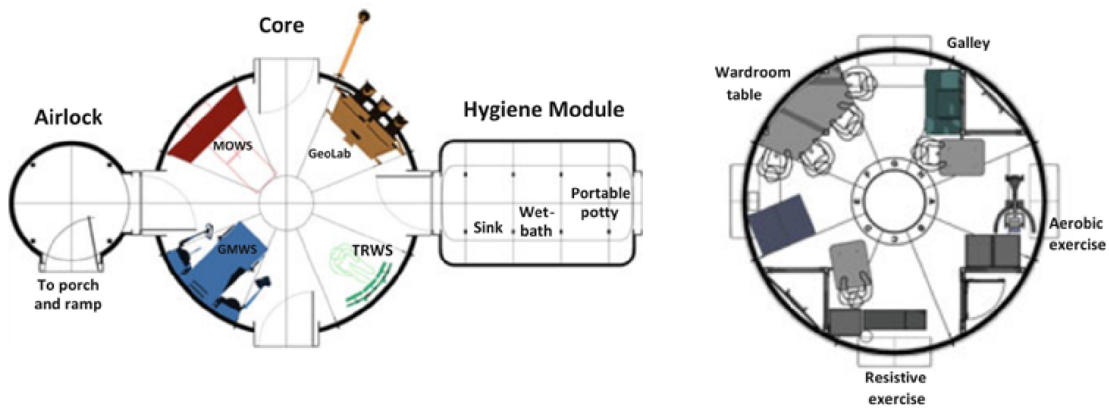

Figure 2.2: Layout of the Habitat Demonstration Unit, in 2012 [15]. First floor is on the left of the picture, second floor on the right.

2.2.3 Designed for humans

When designing space habitats, the psychological needs and the behavior of the crew need to be taken into consideration. The psychological effects of isolation and life in space are notably investigated by the HRP at NASA, in HERA [18].

In order to design comfortable habitats for a manned mission, NASA created Human-Centered Design (HCD) [16]. This approach ensures that the design selected accommodates human capabilities and limitations by involving the users and using their evaluations of the proposed designs to iterate.

Before proposing a configuration to the stakeholders involved, the design has to take into account various parameters, such as the practicality of the layout or the desired/undesired adjacency of different areas. For example, some areas need to be completely isolated, to provide solitude and privacy to the crewmembers [14] (hygiene area, private quarters). Reduced gravity and the resulting postures of the crewmembers [15, 23] are also a challenge because the reference dimensions used on Earth for corridors or furniture are not valid anymore.

Studies have also been conducted to determine the minimum Net Habitable Volume (NHV) for long-term missions. Based on historical data and psychological factors, Subject-Matter Experts (SME) recommended a minimum acceptable NHV of 25 m^3 per person [27]. This NHV is lower than any habitable volume used before for long-duration missions, as shown in Figure 2.3.

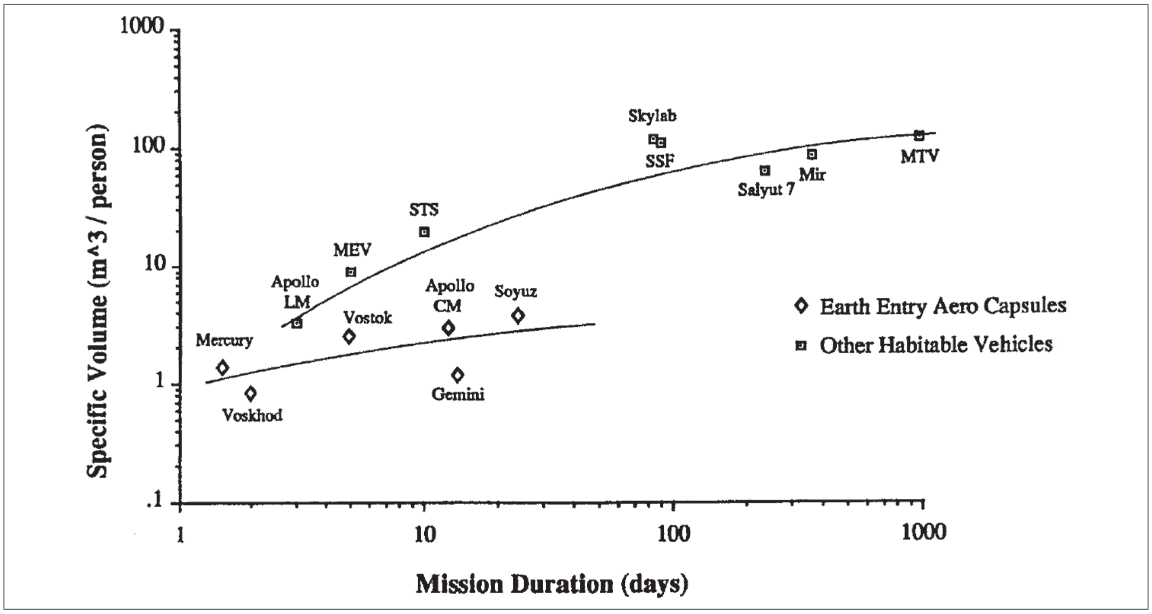

Figure 2.3: Volume per crewmember for historical missions, from [14]

The aforementioned requirements and physical and psychological constraints guide the design process. Understanding their origin helps address them in an intelligent way.

2.3 Design methodology

The space flight project life cycle, as used by NASA, is illustrated in Figure 2.4. It consists of several development phases, from concept studies to preliminary definition, detailed definition, development and finally operations and disposal. The conceptual and preliminary design processes correspond to the first phases of the lifecycle (Pre-A, A and B) of the project. Most of the design choices are made during these first phases. Then, during Phases C and D, the design selected is implemented and tested. It is used during Phase E

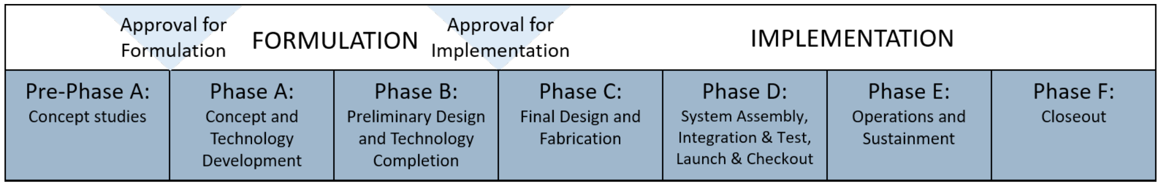

Figure 2.4: Space flight project life cycle, adapted from [28]

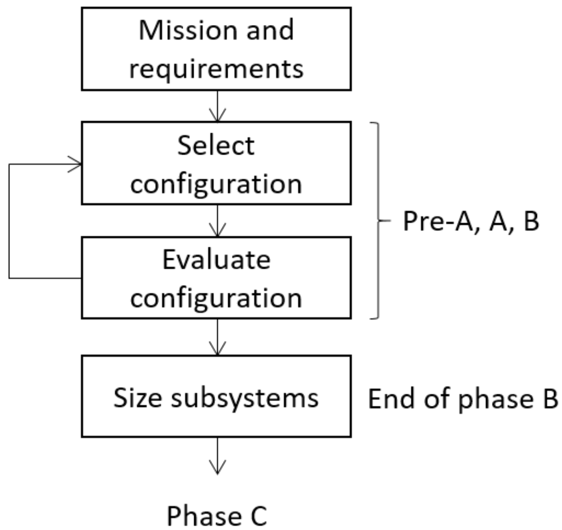

Figure 2.5: Design process for space habitats, derived from [15, 14, 23]

and finally retired in Phase F.

Several processes for space habitat design can be derived from historical methods or found in space architecture manuals [15, 23, 29]. Their similarities allow to identify the overall historical design methodology, presented in Figure 2.5. First, the mission is stated and the requirements derived from the mission outline. Then, during Phase A and the beginning of Phase B, configurations are designed, selected, evaluated and iterated by the stakeholders until they converge on a final design and layout. Finally, during Phase B, a preliminary design for subsystems is selected to meet the requirements. Phases C and D aim to consolidate this design. In particular, this process was used to design the International Space Station [15].

The following subsections describe each step of this process in greater detail.

2.3.1 Stating the mission and deriving associated requirements

Based on the mission statement for the space habitat, requirements can be derived from NASA Space Flight Human-System Standard [22, 17]. NASA Space Flight Human-System Standard is a list of requirements for human space flight missions, that includes all crew activities in all phases of the lifecycle of the spacecraft, both inside and outside of it, in space and on lunar and planetary surfaces. The first volume contains a list of health standards for human performance, whereas the second volume outlines all the requirements linked to the physical and psychological needs of the crew.

This second volume is particularly interesting because it regroups numerous requirements linked to the mission: atmospheric requirements (total pressure, dioxygen, CO_2...), water, food, waste management, and volume necessary to perform the various activities, especially when the astronaut wears a suit.

Psychological requirements are also taken into account, following the guidelines established in [17] for privacy needs, and the minimum NHV [27]. For example, for missions longer than 30 days, it is considered necessary to provide individual private quarters to the crewmembers. Indeed, as the mission becomes longer, the crew needs more recreation space and more privacy, resulting in an overall larger space.

2.3.2 Selecting a configuration

The historical process leading to the creation and selection of a configuration for space habitats is iterative [14]. The main stakeholders (astronauts, engineers, psychologists...) review and criticize the different configurations proposed at each iteration. To do so, several methods are involved.

The process applied to the American Space station "Freedom", which ultimately became the ISS, is described in Figure 2.6 [14]. At each phase, the stakeholders completed an analysis and evaluation sheet that helped understand the disadvantages of each configuration, based on several criteria, such as comfort or safety. It is the historical process used to select a spacecraft configuration.

Another methodology was developed during the Space Exploration Initiative (SEI) in 1990 [14]. It consists in a parametric exploration of the design space, depending on the mission, and an evaluation of the mass and the geometry of the space habitat based on the criteria developed in Section 2.3.1. By performing a topology comparison for different layouts and applying custom metrics to evaluate them, a "best concept" can be selected and improved using the best features of other discarded concepts.

All these methods follow the HCD guidelines provided by NASA in [16].

2.3.3 Sizing subsystems

Once the configuration is selected, based on the mission and the derived requirements, subsystems can be sized and technologies selected. A "subsystem" is a system contained in a larger system. In space habitats, these smaller systems are crucial to provide all resources necessary to the human crew. They can comprise resource tanks (oxygen, water or food), but also various technologies implemented to make the spacecraft habitable. These technologies also contribute in ensuring that regulations (air filtering, for example) are respected and reducing the mass of the habitat (recycling technologies). Thus, the main goals of subsystems, as shown in Figure 2.7, are to [26]:

- Generate and manage power in the habitat
- Control the humidity and temperature in the habitat to keep it habitable at all times
- Regulate the atmosphere composition in the habitat
- Manage human waste
- Produce, process and store food products
- Collect wastewater, recover and transport potable water.

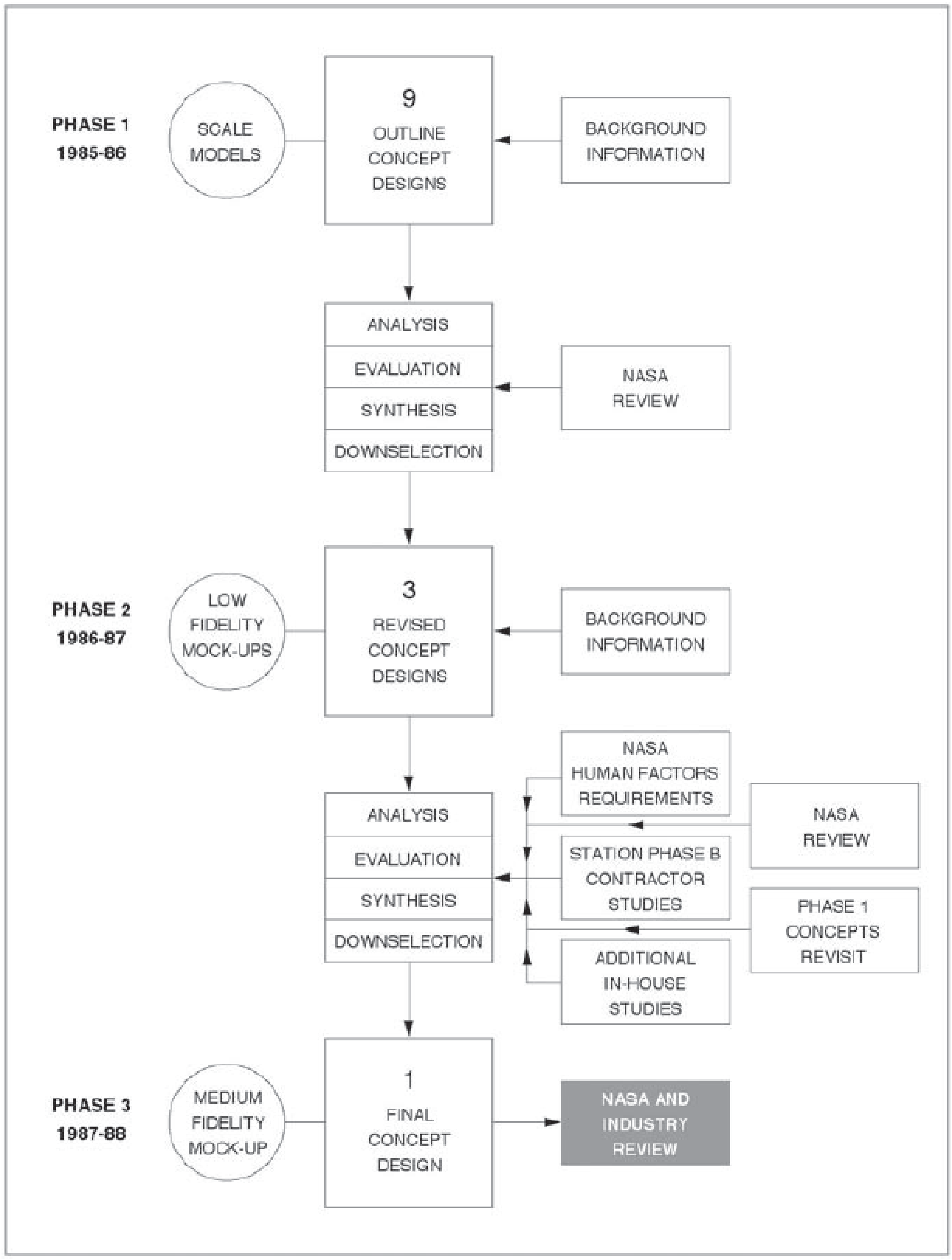

Figure 2.6: Iterative process used to choose a configuration for the American Space Station in 1985-90 [14]

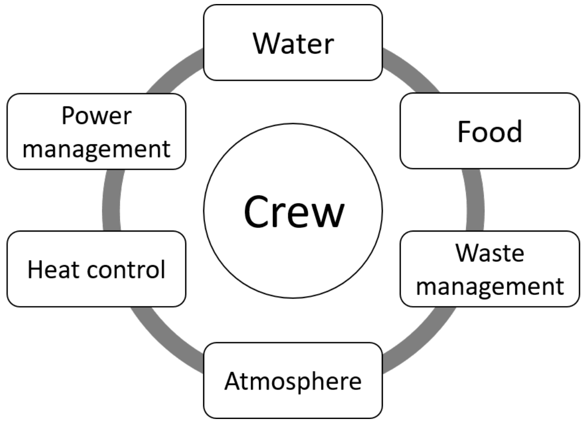

Figure 2.7: Resources managed by subsystems in a space habitat

For very short missions, crews can survive by using power, water, food and oxygen stored in the spacecraft. This category of subsystems is called "open-loop": the stock is consumed by the crew, and a resupply mission needs to be organized if the stock needs to be replenished. For longer missions, like in the ISS, the systems used are “closed-loop”, which means that at least part of the waste created by the crew is recycled. A simple illustration of such a system is the Sabatier reaction, used in the ISS to convert CO_2 into H_2O [30, 31]. Water can also be extracted from ambient humidity, urine or solid waste.

A simplified illustration of how the different Life Support subsystems interact with each other in the ISS is provided in Figure 2.8. All these subsystems must be sized in order to store, produce or recycle enough power, oxygen, food and water for the crewmembers to live in the spacecraft for the complete length of their mission. However, if their size is too important, the costs associated with the mission will rise.

In order to address such a complex problem, NASA developed an Advanced Life Support Sizing Analysis Tool (ALSSAT) [32, 33]. ALSSAT helps users in selecting the best Life Support Systems according to NASA’s criterion, Equivalent System Mass (ESM) [34, 26]. ESM accounts for subsystems mass, volume and power needs. ALSSAT allows its users to perform parametric trade-studies of the different subsystems available.

When the configuration is selected and the subsystems are sized, the preliminary design of the habitat is complete. The design teams can then move to Phase C, which consists in

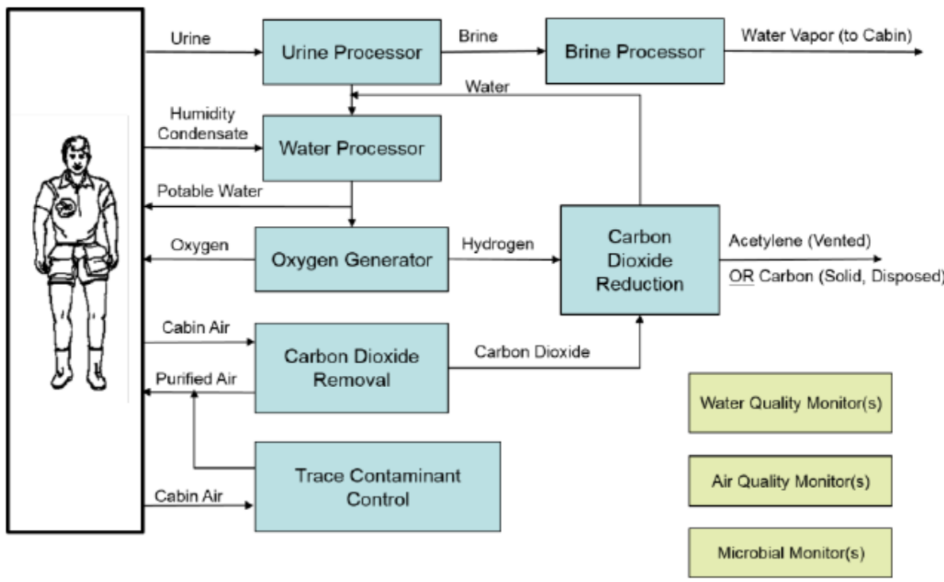

Figure 2.8: Simplified schematics of the Life Support System (LSS) [30]

detailing the design selected.

Subsystems play a great role in both the costs and the reliability of a space habitat. They are vital for the human crew and were estimated to account for around 20% of the mass of the total system during the preliminary study of an inflatable space habitat (mission TransHab) developed by NASA [14]. The next section will focus on the actual methodology and the tools currently used to select a subsystem architecture.

2.4 Subsystems sizing and selection methodology

The methodology for subsystems sizing and selection, can be described as following the generic top-down design process, presented in Figure 2.9. First, the need and the problem are defined. This part is conducted when the mission and its associated requirements are determined. The following four steps will be described in greater detail in the next subsections.

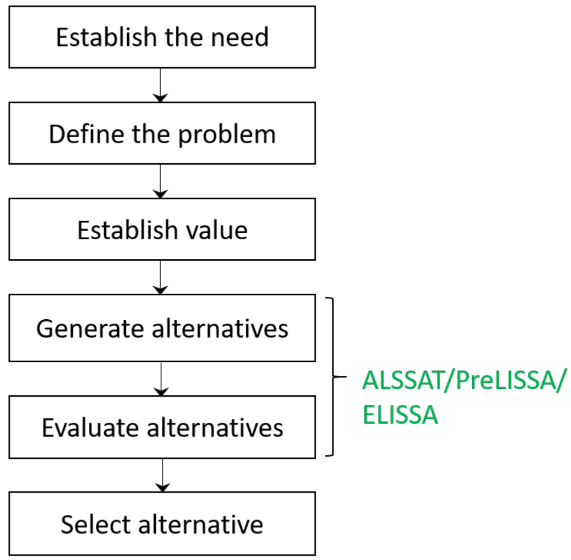

Figure 2.9: Generic top-down design process used for subsystems sizing

2.4.1 Establish value

The main criterion used by space agencies to evaluate the performance of space habitat subsystems is Equivalent System Mass (ESM). ESM not only accounts for the mass M and the volume V of the subsystem selected, but it also considers its influence on power demand P, heat generated C and crew time CT related to the duration of the mission D. Equivalency factors are then used to convert these various elements into a mass [26]. The equation for ESM is:

$$ESM = M + (V \cdot V_{eq}) + (P \cdot P_{eq}) + (C \cdot C_{eq}) + (CT \cdot D \cdot CT_{eq}) \tag{2.1}$$

Equivalency factors are determined for different missions by subject-matter experts in [26]. ESM is used as an Overall Evaluation Criterion (OEC) in both ELISSA [35] and ALSSAT [32].

2.4.2 Generate and evaluate alternatives

In this context, alternatives consist of sets of subsystem technologies that can be used to accomplish the mission. To evaluate these alternatives, these technologies need to be sized.

Two main software packages enable sizing of subsystem technologies: ALSSAT, developed by NASA, and ELISSA, created by the University of Stuttgart, in Germany.

A comparison of ALSSAT and ELISSA is presented in Table 2.2. The University of Stuttgart, while developing the very high-fidelity ELISSA, also developed a lower-fidelity tool, PrELISSA, quite similar to ALSSAT. This tool is also Excel-based and computes a score for each input configuration. Like ALSSAT, it uses the constant values for the inputs and outputs of the subsystems selected.

ALSSAT is a steady-state tool, therefore it is not capable of testing the abilities of a subsystem set to resist to a dynamically-changing planet and crew. For example, Mars is subject to capricious sand storms that can notably incapacitate solar energy production during a long time. Using ALSSAT, this kind of event would be completely overlooked.

Table 2.2: Comparison of existing sizing tools

Capabilities	ALSSAT [32]	ELISSA [35]
Performs sizing	Yes	Yes
Level of fidelity	Low, steady-state	High
Simulation length	Instantaneous	Hours
Multi-mission	No	No
Trade studies	Yes	No
Availability	No	Yes

ELISSA, on the other hand, is very powerful and takes numerous factors into account. It is a dynamic tool, simulating the evolution of the habitat at every second, and offering a large number of options to its users. But ELISSA is very slow, with only one simulation taking hours to run [35].

There is a gap to be filled here. Space habitats need to be resilient, therefore the subsystems sizing method needs to be dynamic, able to simulate failures or events that could prevent the habitat from properly functioning. However, the subsystem sizing method also needs to be fast in order to help users perform trade-offs and simulations. The introduction of new technologies and new scenarios also means a more computationally-expensive sizing process, which would slow the calculations.

Moreover, if space agencies want to develop a base, or a village, like ESA does [12], several habitats will be needed to accomplish a variety of missions. It would be much less costly, in terms of time and money, to size one habitat for these missions and use it several times. In addition, doing so would reduce the need for redundant systems and spare parts. Therefore, to reduce development costs and produce space habitats at a larger scale, it can be interesting to design space habitats for multiple missions. Existing tools do not have the capability of sizing a habitat for multiple missions.

2.4.3 Select alternative

The current selection method is Point-Based Design (PBD). PBD is a method consisting in selecting a single architecture, the only one to be developed and tested for the mission. This point configuration is improved throughout the process, but it is fixed, therefore changes in mission or technology are costly.

When using PBD, following a first analysis using one of the tools available (ALSSAT, PrELISSA or ELISSA), a single architecture is selected at the end of the process. The selected architecture is then detailed, tested and integrated to the habitat in Phases C and D of NASA's Spaceflight Project Lifecycle. This method was used to select the ISS subsystems [15].

The U.S. Navy [36] and companies such as Toyota [37] showed that PBD rarely yielded designs that were eventually developed and used. Indeed, the early elimination of alternatives using low-fidelity tools such as PrELISSA [35] or ALSSAT [32] is not exact or rigorous, so it can lead to sub-optimal designs [36].

Therefore, a way to improve current subsystem selection methods would be to shift from point-based design to another method, allowing to rigorously eliminate less-performing alternatives as the design is detailed and more accurate evaluations are conducted.

The objective of this thesis is to fill the existing gaps in subsystem sizing and technology selection. It is formulated below as:

Research objective:

Create a methodology to dynamically size space habitats subsystems and select technologies for multiple missions.

This leads to the research question this work is aiming to address:

Research question:

How can subsystems be dynamically sized and selected for multiple missions?

The following chapter discusses and further investigates the research question this thesis focuses on. In particular, it formulates hypotheses based on the challenges identified throughout this examination.

CHAPTER 3
PROBLEM FORMULATION

This chapter aims to define hypotheses to answer the research question defined in Chapter 2:

Research question: *How can subsystems be dynamically sized and selected for multiple missions?*

Based on the shortcomings of the current sizing and selection process, we can outline two main ways to improve the design process: by modifying the sizing method and by enhancing the process of technology selection. The first section focuses on the sizing methodology, and in particular on multi-mission sizing methods. The second section concentrates on the challenges brought by point-based design and how a shift to set-based design could help address them.

3.1 The sizing process

As described in Chapter 2, subsystems sizing is crucial in the design process because it enables the evaluation of the performance of the technologies considered.

3.1.1 Subsystems sizing

ALSSAT uses steady-state formulas to size the different subsystems of the habitat, based on the inputs of the mission: crew size, location, duration of the mission [32]. This method being steady-state, it is instantaneous, however it is not capable of evaluating the impact of failures on the system.

ELISSA sizes the different subsystems after a dynamic simulation of the mission, with a time-step of one second. The subsystem design process is discrete and open-loop: each component model has a defined processing capacity, and the number of each component is selected based on the crew size [35]. The tank size is estimated depending on mission parameters and is updated at the end of the simulation based on the results. This process is not iterative, but it still takes several hours.

We can find more elaborate subsystems sizing techniques in the literature, especially in the aerospace field where mass is also critical for design and where subsystems can be very mass-consuming. An example can be found in [38] and represented in Figure 3.1.First, the mission is defined, and associated requirements are derived. Using a matrix mapping the technologies available to the resources needed, the methodology selects an architecture, sizes the power-consuming elements and the power sources, and evaluates the subsystem architecture. It then verifies that the aircraft is able to perform its mission. If it is not the case, an iteration is needed. In the case of an aircraft, it can be done by varying the weight of the subsystems selected [38].

Such a sizing method would be more time-consuming than what is currently implemented in ALSSAT or ELISSA. It would also need to be adapted to space habitat subsystems. In particular, its iteration process would need to be modified to take all subsystems interdependencies into account and to ensure convergence. Therefore, a closed-loop sizing process would be more precise, but also more time-consuming than an open-loop process. As outlined in Chapter 2, ELISSA is a high-fidelity tool but it is too slow to enable easy trade-offs and architecture comparisons. Therefore, this research focuses on developing a faster sizing tool, that enables multi-mission sizing and trade-off analysis.

In order to reduce the time necessary to size a set of subsystems, the level of fidelity of the analysis must also be diminished. The level of fidelity of an analysis tool depends on its time step, the number of parameters and the level of fidelity of the subsystem models. This leads us to our first hypothesis:

Hypothesis 1.1:

If a medium-fidelity dynamic sizing tool for space habitat subsystems is developed, then space habitat subsystems can be sized faster than with state of the art tools.

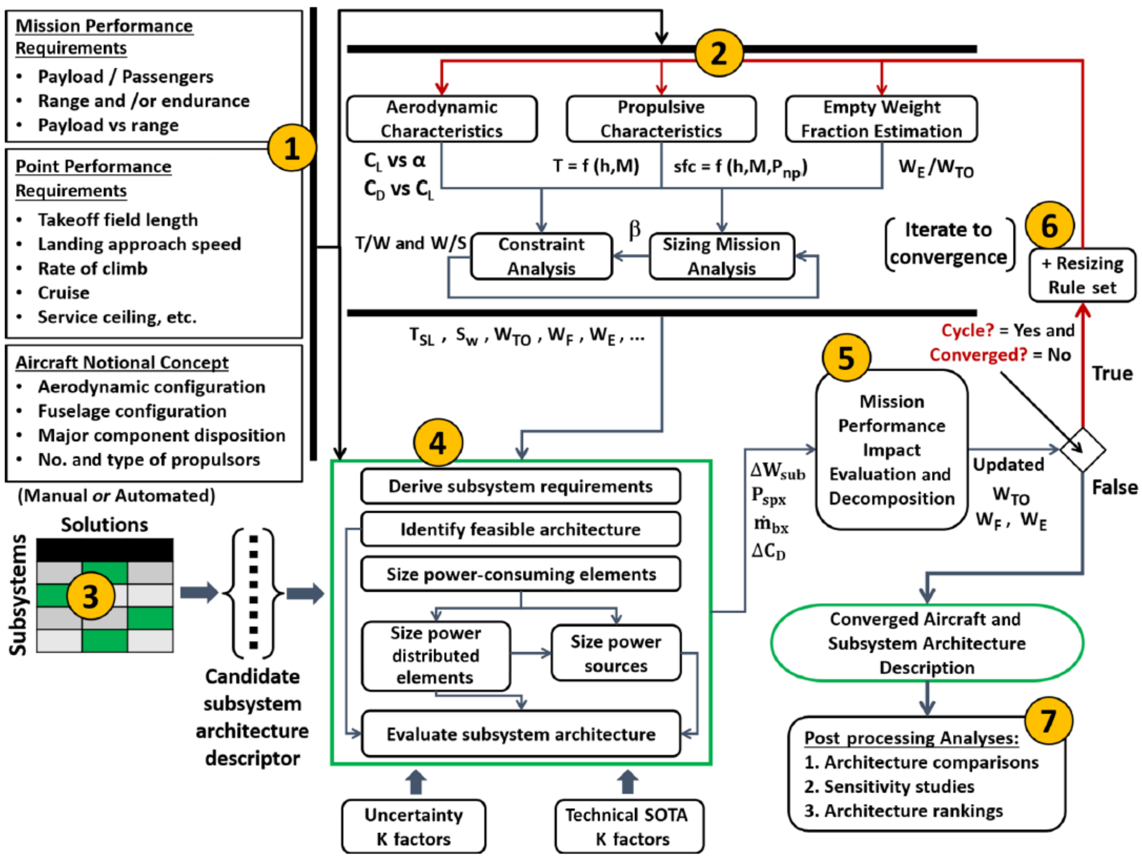

Figure 3.1: Subsystems sizing methodology, from [38]

Table 3.1: Comparison of existing analysis tools, adapted from [1]

	EcoSimPro	V-Hab	BioSim	HabNet
Year of publication	2003	2006	2003	2015
Dynamic ?	Yes	Yes	Yes	Yes
Level of fidelity	High	High	Medium	Medium
Simulation length, for 90 days	Weeks	1 week	seconds	seconds - minutes
Availability	Commercially	Yes	Yes	Yes

This medium-fidelity sizing tool should revolve around an existing medium-fidelity analysis tool, simulating the evolution of the behavior of the different subsystems available.

3.1.2 Available analysis tools

Space habitat subsystems analysis tools dynamically simulate the evolution of the habitat during the mission input by the user. At each time step, they determine the inputs and outputs of each element of the habitat. These inputs and outputs are computed based on the time of the day and the activities of the crew. In the sizing process, they are used to evaluate the architecture selected.

The analysis tool to be selected needs to be available, dynamic and fast. A review of all existing habitation and life support modelling tools, conducted in [1], is summarized in Table 3.1.

Because the intent is to simulate long-term missions, which can last from months to years, both EcoSimPro and V-Hab can be eliminated. Indeed, one simulation using one of these tools would take months to run.

HabNet is an adaptation of BioSim, updated with more recent technologies and crop growth. HabNet is the only tool that was validated against operational data downlinked from the ISS; it was able to predict the most important dynamic phenomena observed in the ISS [1]. BioSim is slightly faster than HabNet as it was developed in Java, whereas HabNet was developed in Matlab.

To ensure accuracy of the results generated through the proposed methodology, HabNet is selected as the tool of choice to be adapted to size subsystem technologies.

A faster sizing method would enable to size habitats for multiple missions, which in turn could help cut development and production costs. The following section will discuss multi-mission sizing and existing methodologies, used in the context of aircraft design.

3.1.3 Multi-mission sizing

During the last twenty years, the U.S. military has changed its focus: instead of designing aircraft or ships to be superior in only one role, the military designs them to fulfill several different purposes [39]. This concept is perfectly illustrated by the advent of the F-35, replacing the F-18 A-F to reduce ownership costs and improve the capabilities of the fighter aircraft [40].

Multi-mission design helps reduce the research and development costs linked to the development of a new product. It also helps diminish the number of assets needed for the different missions they need to fulfill, and therefore diminishes the number of costly acquisitions for the military [40]. Commercial aircraft manufacturers, such as Airbus or Boeing, also create "families" of products to limit their economic investment in research.

Therefore, it seems that multi-mission design for space habitats is the next step towards their long-term development, and maybe their commercialization. In the shorter-term, we can think of ESA's goal to build a Moon village (shown in Figure 3.2), that would certainly require several space habitats to be linked together. Designing one habitat for several different missions from the beginning would curb the research and development costs and the same design could be used for several habitats in a village, even if they do not have the exact same mission. Using multi-mission habitats to build a village could also help reduce the number of spare parts needed and, consequently, lower the total mass that would need to be sent to the Moon.

Figure 3.2: The Moon village, as envisioned by ESA

In the context of this research, a mission can be defined by a location, a duration, a crew, and on-board activities such as research experiments, Extra Vehicular Activity (EVA), technology testing, and others. In the context of this research, multi-planetary sizing is not considered because the environmental conditions (between the Moon and Mars, for example) would vary too much for a single-design to be cost-efficient.

3.1.4 Existing multi-mission sizing processes

Several methods have been developed to size multi-mission assets. In [39], a methodology is developed to size a multi-mission Navy aircraft, named the Gryphon. It uses Response Surface Methodology (RSM) to model the outputs of the aircraft sizing tool and investigate the mission space. It calculates which portions of the design space satisfy all requirements, from all missions. Then, users can select an architecture from the feasible design space.
In [41], a generalized methodology is developed to size unconventional aircraft using several design points. The sizing method is depicted in Figure 3.3. It consists in sizing the concerned module for each design point, and selecting the maximum scaling parameters among all those yielded by the sizing loop for the different point considered. The maximum scaling parameters are selected because they generally refer to values that increase when demand increases for the module - for example, in the context of this work, a bigger water tank will be capable of supplying more water than a smaller one. Therefore, using

the maximum scaling parameter helps converge to the sized module for all design points investigated.

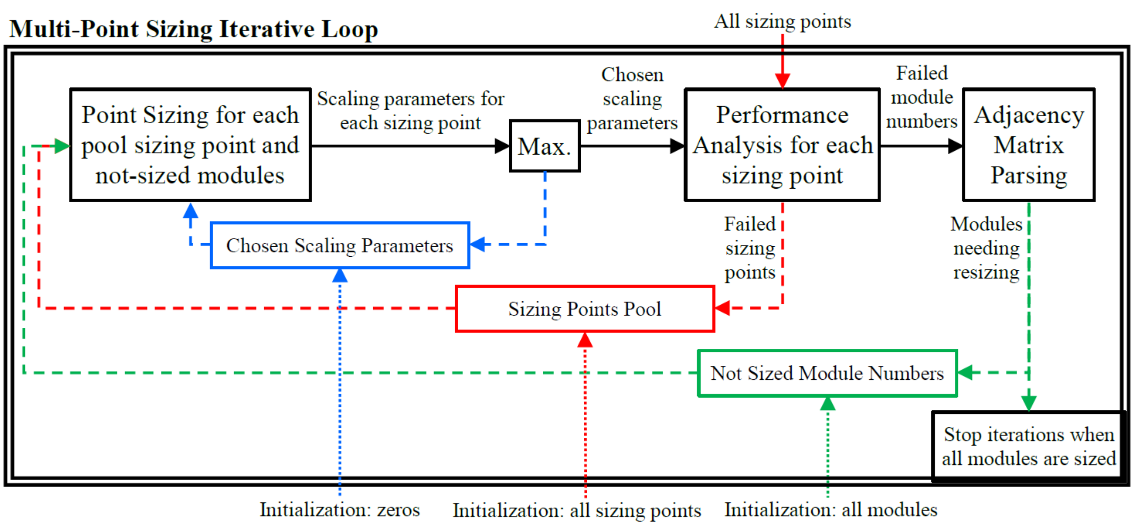

Figure 3.3: Multi-point sizing methodology developed in [41]

Both methods are generic and can be adapted to space habitat subsystems. They both investigate the regions of the design space that satisfy all requirements. However, instead of defining the design space in which the subsystems are able to fulfill all input missions, it directly sizes all systems to meet all the requirements linked to the multiple missions they need to satisfy. For each technology set, it would only propose one sized architecture to the user, that would not necessarily be the "best" in terms of the users criteria. For example, in the case displayed by Figure 3.4, the second sizing method presented would only output one design, whereas the design space exploration reveals that several non-dominated designs are available.

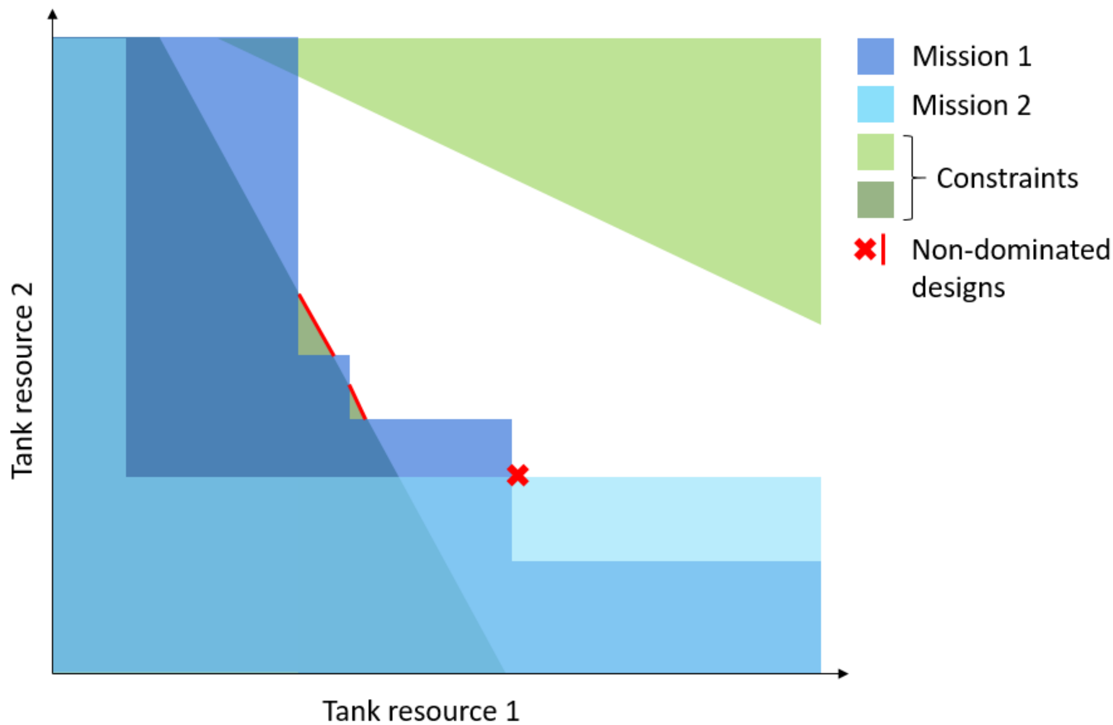

Figure 3.4: Design space exploration, showing several non-dominated points

Consequently, in order to select the best set of technologies for subsystems, the methodology developed in [39] seems to be more appropriate than the multi-mission sizing process outlined in [41]. The multi-mission sizing methodology found in [39] could be adapted to space habitat subsystems in order to size habitats for several missions concurrently. This leads to the formulation of a second hypothesis:

Hypothesis 1.2:

If a design space-investigating multi-mission sizing methodology is adapted to space habitat subsystems, then it can help sizing them for several different missions concurrently.

The design space exploration process mentioned could be developed in various ways. In particular, the single-mission sizing method described in Section 3.1.1 could be leveraged. Using the open-loop method mentioned, the resource tanks and the power generators could be sized for each of the n input missions. For these elements, multi-mission sizing could consist in:

$$Size = max_{mission\ i=\{1,\dots,n\}}(Size_{mission\ i}) \tag{3.1}$$

Indeed, oversized tanks or an oversized power generation facility should not endanger the mission, as it means that more resources are available to the crew. This assumption was also used in the second multi-mission sizing method presented in this section and depicted in Figure 3.3. This formulation of the sizing methodology leads to another hypothesis:

Hypothesis 1.2.1:

Space habitat storage can be sized for multiple missions by retaining the maximum size of storage obtained with single-mission sizing.

If it is validated, this hypothesis could help implement the design space exploration multi-mission sizing method mentioned in **Hypothesis 1.2** using the single-mission sizing tool developed to validate **Hypothesis 1.1**.

A fast sizing multi-mission methodology can provide numerous feasible architectures to decision-makers and facilitate the comparison of the different alternatives available. In order to make an informed decision and choose the best combination of technologies, stakeholders could use this new capability to improve their current selection method.

3.2 Architecture selection

3.2.1 Technologies relevant to space habitats

Since the development of the very first space habitats (Apollo, Mir, the ISS), numerous subsystem technologies have been explored, developed and even tested on the ISS. Nowadays, several biological and chemical processes are being investigated by NASA [30] and other laboratories such as Texas Tech University [42].

For example, technologies such as Plasma Pyrolysis (PPA) and Metal hydride separation would increase oxygen recovery from the Sabatier chemical reaction (used on the ISS to produce oxygen) by partially recycling its byproducts [43]. The Bosch process could completely replace the Sabatier process, producing less byproducts [31]. Auto-cleaning filters for trace contaminate and particulate control would reduce the need for maintenance [30]. Texas Tech University also develops a bioreactor that biologically treats urine. It limits the use of hazardous chemicals that need resupply and creates useful byproducts [42].

When it comes to new technologies, another promising field of subsystem research is energy generation. Indeed, today, in space, energy is generated using solar panels. However, solar panels are dependent of the position of the habitat with regard to the Sun, and they can be deteriorated by dust storms for example. Therefore, it can be limiting to rely only on one power source, especially when it is as environment-dependent as solar panels are. Therefore, efforts are made to develop more reliable and diverse energy generation systems [44]. A graph of recommended power generation systems depending on the power needed and the length of the mission is presented in Figure 3.5.

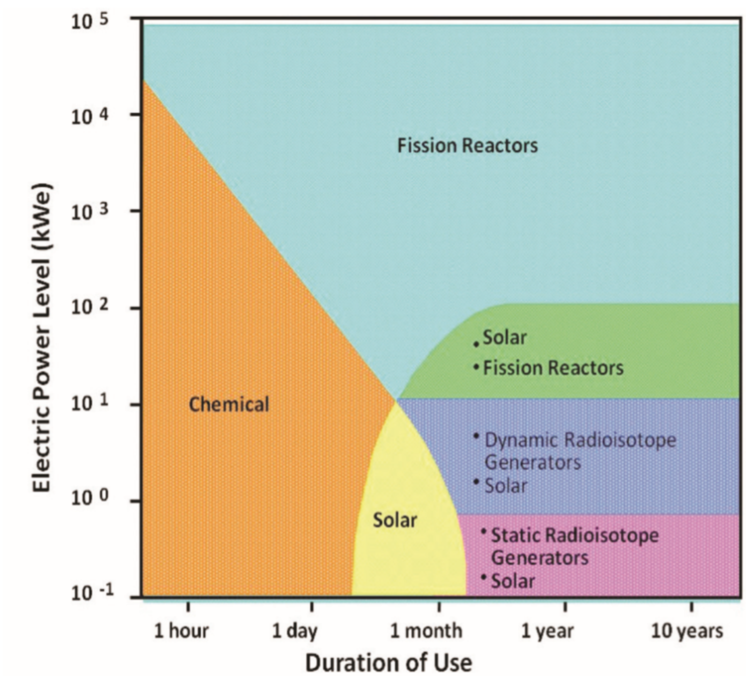

Figure 3.5: Map of power generation systems for space missions depending on the power required and the duration of the mission [44]

These new technologies are key to the creation of sustainable long-term space habitats. However, as the number of technology candidates increases, it becomes more and more difficult to assess their impact on the system and compare them.

The design methodology used for the ISS and the HDU is Point-Based design [14, 20]. This process consists in selecting an architecture using multi-criteria decision methods and modifying the design to meet the objectives. However, this methodology has proven to lack efficiency for the Navy [36], because the architecture selected at the beginning of the process rarely ended up being the final design. The introduction of additional technologies to select from makes the process of picking and developing only one alternative even less likely to provide an interesting outcome.

3.2.2 Set-based design

During the past few years, the U.S. military reformed its design methods, starting to implement "set-based design" (SBD) to avoid making uninformed decisions in the first design phases. Set-based design is a design process used during the conceptual and preliminary design phases. It consists in developing and comparing several alternatives in parallel and eliminating those proven less performing than the others [36, 45]. The architectural choices, that locked costs and design possibilities very early in the process, are postponed. Set-based design allows to compare ranges of options so design teams can understand the influence of several parameters on performance and cost. Moreover, using SBD, the choice made to eliminate designs is always supported by tests and experiments, which makes it more rigorous and traceable than Point-based design.

Set-based design was experimented in several different areas, from the military [36] to the car industry [37] to industries dedicated to smaller products like graphic products and electronic systems [46]. Studies assessing the impact of SBD showed a positive outcome on the product cost, the level of innovation of the product, the number of changes and the level of risk of the project [46]. This methodology could also help decision-makers determine which of the subsystem technologies currently under development could really improve the state-of-the-art habitat and decide how to distribute research funding.

Set-based design can be facilitated by an environment that helps users visualize the impact of their choices. By displaying insightful data, it can support the user's design choices. If the environment is interactive, *i.e.* able to update instantaneously when the inputs are modified, the user can better understand the impact of trade-offs and make associated decisions. Therefore, the development of a parametric trade-off environment may help stakeholders make more informed decisions based on trade-offs and analysis of the impact of different parameters on performance. By using the outputs of such an environment, SBD could be used in a rigorous and repeatable way, setting a standard selection methodology for conceptual design where all decisions are justified and traceable. It is a first step towards set-based design. This leads to another hypothesis:

Hypothesis 2:

If we support design decisions using trade-off analysis, we can leverage set-based design for space habitat subsystems during the conceptual design phase.

These three hypotheses aim to provide an answer to the research question formulated in Chapter 2. In the next chapter, an approach is proposed to test these hypotheses.

CHAPTER 4

PROPOSED METHODOLOGY

This chapter presents the steps proposed to test the three hypotheses developed in Chapter 3. The proposed methodology for subsystems selection follows an adaptation of the generic top-down design support process presented on Figure 4.1. It is compared to the current methodology, adapted from the method proposed by the Institute of Space Systems, in Stuttgart, which developed ELISSA, in [35]. The new process aims to generate multi-mission alternatives, to evaluate them and to facilitate the selection of a set of alternatives, which will be developed further and compared until one alternative is selected.

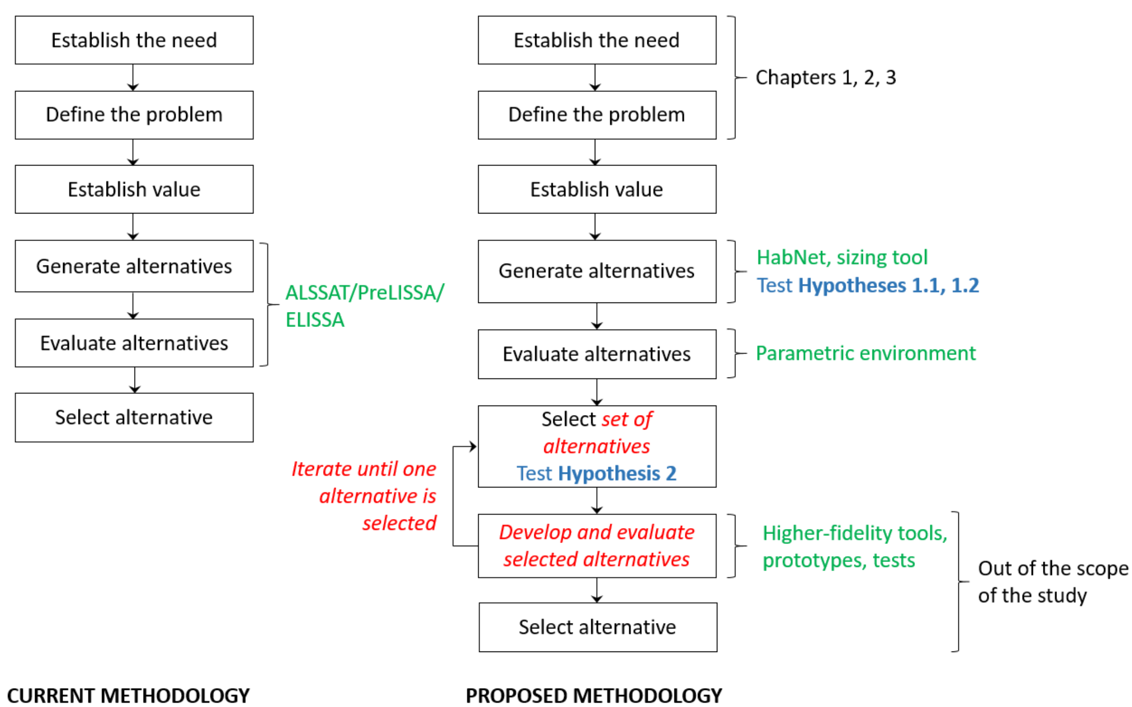

Figure 4.1: Current and proposed methodology for space habitat subsystems selection

The first three chapters aimed to define the need for a new methodology and the objective of this research: *Create a methodology to dynamically size space habitats subsystems and select technologies for multiple missions*. In Chapter 2, the existing methodology was described and some of its gaps were highlighted in Chapter 3. Based on these observations, we formulated four research hypotheses:

Hypothesis 1.1: *If a medium-fidelity dynamic sizing tool for space habitat subsystems is developed, then space habitat subsystems can be sized faster than with state of the art tools.*

Hypothesis 1.2: *If a design space-investigating multi-mission sizing methodology is adapted to space habitat subsystems, then it can help sizing them for several different missions concurrently.*

Hypothesis 1.2.1: *Space habitat storage can be sized for multiple missions by retaining the maximum size of storage obtained with single-mission sizing.*

Hypothesis 2: *If we support design decisions using trade-off analysis, we can leverage set-based design for space habitat subsystems in a rigorous and repeatable way.*

To test these hypotheses, we need to implement the remaining steps of the design method presented in Figure 4.1:

- Step 3: Establish value: select the decision criteria used to compare and rank the different space habitat subsystems considered
- Step 4: Generate alternatives: in order to generate feasible alternatives, they need to be sized for their mission; **Hypothesis 1.1** and **Hypothesis 1.2.1** will be tested, and a multi-mission sizing process will be implemented to test **Hypothesis 1.2**
- Step 5: Evaluate alternatives: sized systems will be compared using the criteria defined in Step 3.
- Step 6: Select set of alternatives: using visualization of the design space and rankings of the systems considered, a rigorous selection methodology will be defined and **Hypothesis 2** tested

- Step 7: Implement and evaluate selected alternatives: compare pre-selected designs using higher-fidelity tools and other tests such as analog missions and eliminate alternatives until one remains

- Step 8: Select alternative to be implemented based on the results

Steps 7 and 8 are out of the scope of this study. The following sections will discuss Steps 3 to 6 in greater detail.

4.1 Establish value

As described in Chapter 2, the main performance criterion for space habitat subsystems is Equivalent System Mass (ESM). ESM not only accounts for the mass M and the volume V of the subsystem selected, but it also considers its influence on power demand P, heat generated C and crew time CT related to the duration of the mission D (see Equation 2.1). Equivalency factors are then used to convert these various elements into a mass [26].
These equivalency factors are determined for different missions by subject-matter experts in [26]. For example, the equivalency parameters for a Mars mission are presented in Figure 4.1.
In this research, we tried to use equivalency parameters defined by subject-matter experts only. To do so, the missions input in the experiments conducted to validate the different hypotheses originate from the literature. For example, in [26], the equivalency parameters for solar photovoltaic power generation is only available at equatorial sites on the Moon and on Mars. Therefore, should solar photovoltaic power generation be used, the tests will be run for habitats on equatorial sites.

		Assumptions		
Parameter	Units	Lower	Nominal	Upper
Transit				
Shielded Volume	kg/m³		215.5 (1)	219.7 (1)
Unshielded Volume	kg/m³		9.16 (1)	13.40 (1)
Power	kg/kW		237 (2)	
Thermal Energy Management: Thermal and Cooling	kg/kW		60 (3)	70 (3)
Crewtime	kg/CM-h	1.14 (4)	1.14 (4)	1.54 (4)
Surface				
Shielded Volume	kg/m³		215.5 (1)	219.7 (1)
Unshielded Volume	kg/m³		9.16 (1)	13.40 (1)
Power	kg/kW	54 (2)	228 (2)	338 (2)
Thermal Energy Management: Thermal and Cooling	kg/kW		146 (3)	170 (3)
Crewtime	kg/CM-h	1.25 (4)	1.25 (4)	1.50 (4)

Table 4.1: Table of equivalency parameters for ESM, for a mission to Mars, from [26]

ESM is used as a general criterion to size subsystems, but it is necessary to keep in mind that it does not measure reliability, maintainability or safety [34]. Several other criteria can be added, such as a maintainability index or the Technology Readiness Level (TRL) of the subsystems considered. In this research, the criteria selected are TRL, maintainability and safety. Their values are assumed and used for demonstration purposes only.

4.2 Generate multi-mission alternatives

In order to generate space habitat subsystems that are able to fulfill multiple missions, a sizing methodology first needs to be implemented. Then, using this sizing process, a multi-mission sizing method can be developed.

4.2.1 Sizing methodology

The sizing methodology revolves around an analysis tool, that simulates the behavior of the space habitat. Based on the comparison conducted in Chapter 3, HabNet was selected. To size the subsystems, an open-loop sizing process is implemented, inspired by the sizing methodology used in ELISSA [35]. The method proposed is illustrated in Figure 4.2.

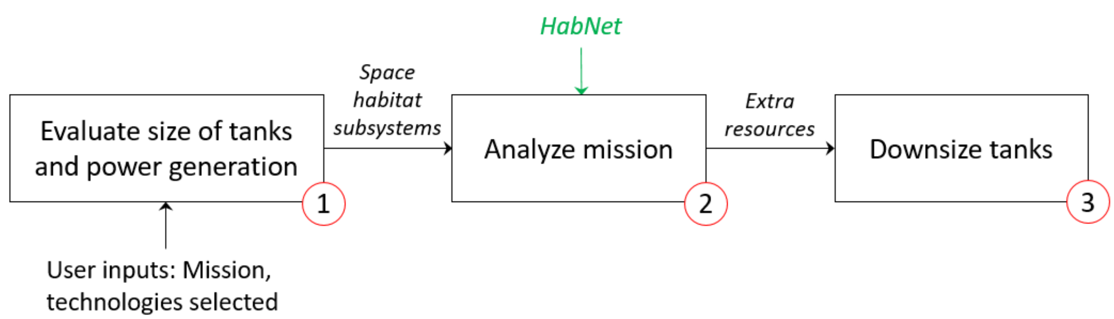

Figure 4.2: Proposed open-loop sizing method for space habitat subsystems, inspired by [35]

First, the components are sized based on the processing capacity needed to host the crew size selected. To this end, literature can be used. During this step, the tanks must be over-sized rather than under-sized, as under-sizing them leads to the death of the crew and an interruption of the simulation [1]. At this point, the analysis is conducted, using HabNet. HabNet returns the evolution of the quantity of the different resources available in the habitat along the mission simulated. Based on these results, if needed, the size of the tanks can be reduced to decrease the overall mass of the system. As an example, if, at the end of the mission, there are 100 liters of water left in the tanks, they are considered to be an extra resource: these 100 liters are not necessary to the success of the mission. Therefore, to limit the mass of resources to be transported to the habitat (and, consequently, its cost), the water tanks can be downsized.

The tool developed can be tested by verifying that this methodology yields a design able to fulfill the mission with HabNet, which is the only available analysis tool that was validated using ISS data [1]. If the verified sizing process takes less time than ELISSA to size a habitat, then **Hypothesis 1.1** is validated. This process can then be included in the multi-mission sizing method.

4.2.2 Multi-mission sizing

An adaptation of the methodology developed in [39] and discussed in Chapter 3 is implemented. The proposed approach consists in three steps.

The first step is to create surrogate models for the sizing tool discussed previously. Surrogate models allow to reduce computation time. Then, **Hypothesis 1.2.1** will be tested by running a sample of random cases and verifying that the elements of the habitat are sized using equation 3.1, for two missions. The equation method can then be generalized to n missions. Finally, based on the requirements derived from the user inputs and using surrogate models of the design parameters, constraint surfaces in the design space can be computed. The design parameters and the design space will vary depending on the technologies selected by the users. In the feasible design space, output by the analysis, all designs will be sized for the input missions. An example of design space exploration, as implemented using **Hypothesis 1.2.1**, is displayed in Figure 4.3.

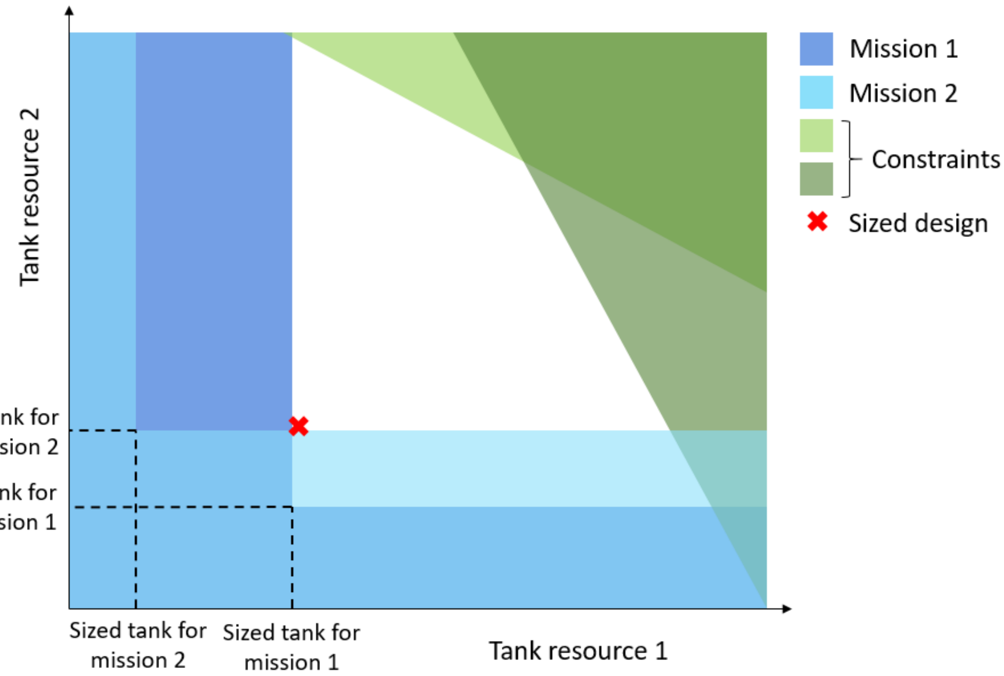

Figure 4.3: Two-dimensional design space using **Hypothesis 1.2.1**

Hypothesis 1.2 can be tested by verifying that this methodology yields a design able to fulfill the different input missions with an analysis tool such as HabNet [1].

The feasible design space can vary greatly depending on the technologies selected by the users. The evaluation and comparison of the different subsystem alternatives will enable stakeholders to make informed decisions.

4.3 Evaluate alternatives and select set of alternatives

In order to evaluate the technology alternatives for space habitat subsystems, the criteria described in Step 3, namely: Equivalent System Mass (ESM), maintainability, safety and TRL are be leveraged. These criteria can be weighted using user preference.

This evaluation must help the user make decisions, and particularly select a set of designs to be pursued in the context of SBD. Therefore, the different evaluations can be displayed in a parametric environment, showing insightful data that can help rigorously eliminate some alternatives. The inputs and outputs of such environment are summarized in Table 4.2 and further discussed below.

4.3.1 Inputs of the environment

Users should be able to assign a mission in the environment. Notably, they should have the ability of varying the duration of the missions on a given celestial body, the number of crewmembers the habitat will need to host, the number and length of EVAs planned, and the needs and potential byproducts of the research experiments conducted on-board.

To define the design space, users must also select the technologies they want to evaluate. Indeed, the main purpose of this parametric environment is to assess and compare the performance of the technologies available or in development. The baseline with no technologies selected would consist in a habitat with no “closed-loop” systems, which means that tanks would provide resources such as oxygen or water and store the crew rejections (carbon dioxide, urine, sweat...). Energy would be stored in batteries.

The environment also proposes several criteria, the main one being ESM, as recommended by NASA [34]. Technology readiness, maintainability and safety are also represented and users can input weights based on their own requirements.

4.3.2 Outputs of the environment

In order to better understand the impact of the different technologies available for space habitat subsystems, the environment displays, among other things, a Principal Components Analysis to evaluate the impact of each technology, a visualization of the design space to help the user choose between several non-dominated solutions and a ranking of the best performing sized sets of subsystems based on user-weighted criteria. The list of inputs and outputs presented in Table 4.2 is non-exhaustive, as other capabilities can be added to the environment. The environment updates instantaneously, or in a short span of time, when

Table 4.2: Inputs and outputs of the proposed parametric environment

Inputs	Outputs
Number of missions to perform	Principal Components Analysis
Mission duration	Ranking of best-performing sets of subsystems
Size of crew	Visualization of design space and Pareto frontier
Crew activities	
Technologies selected	
Weights for criteria	

input parameters are varied.

This environment can be used to select sets of designs by rigorously eliminating less-performing combinations of technologies. To do so, a trade-off analysis is used. During this first iteration of set-based design, the elimination of alternatives is conducted based on rankings of the different solutions and on the Pareto analysis. Less-performing solutions are eliminated.

If the selection method follows the principles of set-based design, then **Hypothesis 2** will be validated.

Then, the methodology presented can be applied to a given mission. This thesis will focus on lunar habitats.

4.4 Application of the methodology: presentation of the use case

In order to verify that the methodology is able to provide insight on relevant missions, it should be used to select habitat subsystems for hypothetical missions on the Moon.

This section focuses on a lunar habitat that is part of a lunar base located in the equatorial plan. Settling on the equator has its advantages: it is the easiest site to land and launch from and it facilitates communication with Earth. The downside is that lunar nights reduce the exposition of solar arrays to the Sun [12]. There are other advantages to being deployed at a pole, where ice is more abundant and can be used for ISRU (In-Situ Resource Utilization) [12, 47]. For the mission selected, the habitats are located at the equator.

The habitat hosts four to six crewmembers, as assumed in most lunar habitat studies. In particular, it is the crew size used in NASA's Life Support Baseline Values and Assumptions Document [26, 48]. Similar to the ISS, we can assume that shifts will last about 5 to 7 months [15, 48].

For demonstration purposes, this habitat is sized for two different missions, involving different research activities. These activities comprise IVAs (Intra-Vehicular Activities) that can consist in physical, chemical and biological experiments, along with EVAs. They can require different amounts of energy and other resources. For example, the installation of a greenhouse would require special conditions such as light, heat, water and a regulated atmosphere. These needs are evaluated before the sizing and input by users. The resulting architectures are compared for different weightings of the criteria and several sets of subsystem technologies.

These two missions are use cases for the sizing tool, the multi-mission sizing methodology and technology selection. The following two chapters describe the implementation of the sizing tool and its use in the context of multi-mission sizing (Chapter 5) and the technology selection using trade-off analysis (Chapter 6).

Table 4.3: Missions implemented to test the hypotheses presented

Characteristics	Mission 1	Mission 2
Mission duration (days)	210	150
Number of crew	4	6
Number EVA/week	2	2
Length of EVA (hr)	8	8
IVA	input oxygen: 0.5 mole/hr input water: 0.05 L/hr input power: 100 W/hr output oxygen: 0 mole/hr output water: 0 L/hr output power: 0 W/hr output CO_2: 0.4 mole/hr output grey water: 0.01 L/hr output dirty water: 0.04 L/hr	input oxygen: 0 mole/hr input water: 0.02 L/hr input power: 300 W/hr output oxygen: 0 mole/hr output water: 0 L/hr output power: 0 W/hr output CO_2: 0 mole/hr output grey water: 0.02 L/hr output dirty water: 0 :/hr
ISRU production	water : 0 L/hr oxygen : 0 moles/hr	

Technologies (for sizing)	Activation rate OGA: 0.4 Activation rate VCCR: 1 Activation rate WPA/UPA: 0.4 EMU CO_2 removal technology: RCA (Rapid Cycle Amine) EMU Urine management technology: MAG (Maximum Absorbency Garment) Power source: Solar

CHAPTER 5
ADAPTING THE ANALYSIS TOOL TO SIZING

In this chapter, the steps taken to implement the methodology presented in Chapter 4 are presented. Before developing the tools necessary to follow the process, HabNet was adapted to sizing and selection purposes. Then, each step of the method was developed and used to design habitats for the case of study presented in Table 4.3.

The tool selected for the purpose of developing the methodology, HabNet [1], is a simulation tool. Therefore, it was designed to simulate a mission in a given habitat and analyze the evolution of different resources and elements in the habitat as time evolves. Before starting to develop the sizing methodology, the tool needed to be adapted for sizing purposes. Some of the probabilistic elements of the tool were removed and partial activation of the different recycling technologies embedded in HabNet was enabled. The tool was also modified to take more input parameters into consideration.

5.1 Reducing stochasticity

HabNet uses randomness in two main ways. The first one is that the EVAs are distributed randomly in the crew's schedule. This allows sometimes for a small discrepancy between simulation results for the same mission.

The second point is the most interesting for sizing. As the mission goes, if astronauts experience inconveniences (thirst, hunger or CO_2 poisoning, for example), they are attributed a corresponding probability of death, ranging between 10^{-6} and 1. If the inconvenience lasts for several consecutive periods of time, the probability of their death increases.

The purpose of modifying HabNet is to size the tanks, therefore the amount of resources available to the astronauts must be large enough for them to accomplish their mission. Consequently, the mission is now considered a failure if the astronaut experiences any inconvenience, which translates to a probability of death larger than 10^{-6}. The mission also fails if there are not enough resources to entirely conduct the mission (IVAs and EVAs).

5.2 Partial activation of recycling technologies

The ECLS technologies implemented in HabNet, along with the flow of resources between the components, are represented in Figure 5.1.

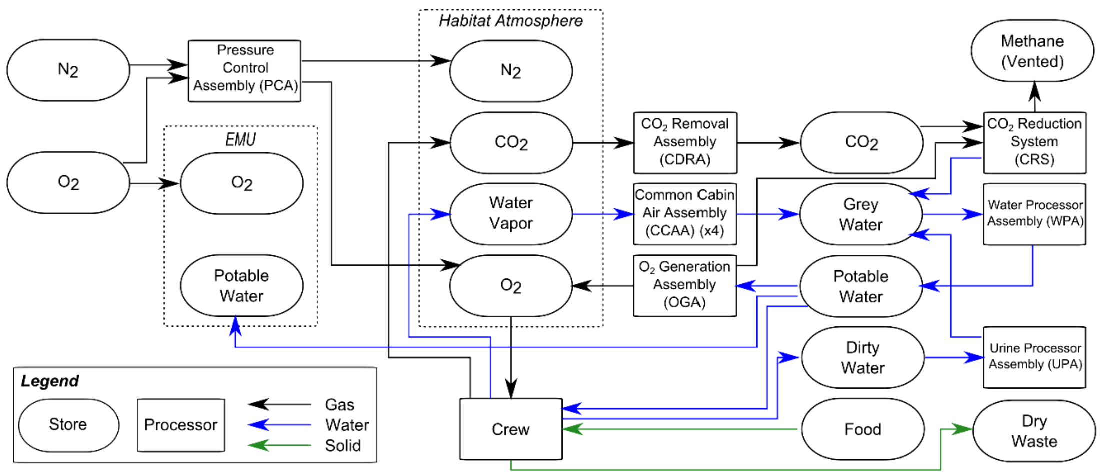

Figure 5.1: ECLS Architecture based on the ISS, as implemented in HabNet [1]

The recycling and processing technologies implemented in this version of HabNet are:

- Pressure Control Assembly (PCA): the PCA ensures that the pressure is acceptable in the different rooms of the habitat, through a closed-loop control system.
- CO_2 Removal Assembly (CDRA): CO_2 adsorption process, removing CO_2 from the pressurized habitat
- Common Cabin Air Assembly (CCAA): dehumidifier, condensing the water vapor in the atmosphere and delivering condensate to the waste water bus for recycling
- O_2 Generation Assembly (OGA): electrolysis of water to produce oxygen and hydrogen

- CO_2 Reduction System (CRS): reacts hydrogen gas produced by the OGA and carbon dioxide to generate water using the Sabatier reaction
- Urine Processor Assembly (UPA): processes dirty water (urine) and turns it into urine condensate
- Water Processor Assembly (WPA): processes and filters grey water (urine condensate, humidity condensate, CRS products), outputs potable water.

All these technologies are used on the ISS and their models in HabNet were validated against data down-streamed from the International Space Station [1]. In the context of sizing, it can be interesting to understand how the level of recycling used in the habitat influences the total resource consumption. If limiting the recycling capacity of theses technologies does not increase the need for resources, said technologies could be downsized, leading to a decrease in weight. For this reason, an activation level was implemented for: CO_2 Removal Assembly, to study what kind of missions the existing technology can support and how tuning down the CDRA can influence the outcome of the mission; O_2 Generation Assembly (OGA) and Water and Urine Processing Assembly (WPA/UPA), to investigate the influence of these technologies on resource needs. This choice was made based on the amount of information available about the different systems.

As an example, let us focus on the activation rate of the Oxygen Generation Assembly. One of the attributes of the OGA is its maximum production rate [49], which is worth a little less than 12 moles per hour. An activation rate is introduced to represent the level of activation of the OGA, so that:

New maximum rate of production = Maximum rate of production * Activation Rate

This new maximum rate of production constrains the oxygen generator. Assuming that the OGA consumes power linearly between its idle state and maximum production state, constraining the oxygen generator also limits the amount of power consumed. The effect of such a constraint on the production of oxygen can be illustrated by Figures 5.2 and 5.3.

The amount of O_2 produced by the OGA saturates at an Activation Rate around 0.15.

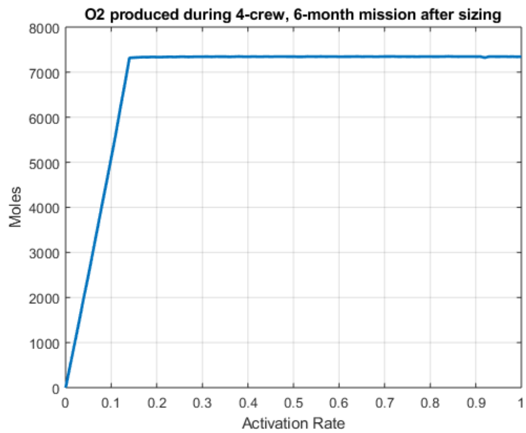

Figure 5.2: Evolution of O_2 production with OGA activation rate

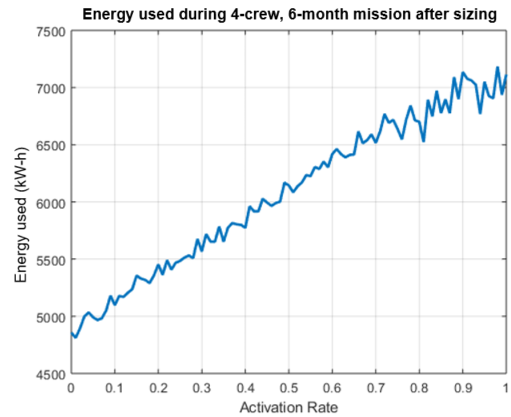

Figure 5.3: Evolution of power consumption with OGA activation rate

During the implementation of the OGA activation rate, it was noticed that the amount of oxygen consumed by the astronauts in HabNet was much inferior to the numbers provided by NASA [26, 48]. For an average heart rate of 80 beats per minute for a day, the mass of oxygen consumed by an astronaut in HabNet is 0.202 kg/day, as opposed to the number provided by NASA, which is more than 4 times higher. With several medical and aerospace papers supporting the numbers provided in HabNet [50, 51], it was decided not to change the crew needs in oxygen.

5.3 Making the tool more parametric

HabNet is a partially parametric tool. Most inputs are hard-coded but can easily be modified. However, some of the mission inputs described in Table 4.2, such as the needs and the outputs of the crew activities or the number of crew, were not available or not modifiable. Aiming towards a sizing method, HabNet was modified to take a list of parameters as inputs. This list includes the initial size of the tanks, the technologies selected, the mission parameters and the amount of resources produced “in-situ”. The complete list of HabNet’s inputs can be found in Appendix A. The tool outputs a data table listing the states of all spaces in the habitat, at all times.

To add the capability of varying the size of the crew for the mission without adding too many inputs, it was decided to use a single model of astronaut: male, 35 years old, weighing 75 kilograms. In HabNet, this data is mainly used to compute the amount of food needed by the crew. Other models of astronauts can be added in the future to improve the modeling accuracy.

As described in [25, 26], most of the crew's mission consists in what is called IVA: Intra-Vehicular Activities. These activities are divided into 6 categories [52]:

- Biology and biotechnologies: studying how living organisms react to different conditions. These experiments can need oxygen, carbon dioxide, water and power, they can reject carbon dioxide, oxygen, and grey or dirty water
- Earth and space science: observing space phenomena. These experiments usually need power to operate the cameras and other observation instruments
- Educational activities
- Human research: the focus if to better understand the risks for human health associated to a space mission. These experiments usually need power to measure vitals and try countermeasures to these risks
- Physical science: studying the long-term physical effects in the absence of gravity
- Technology-testing: testing new technologies developed for space applications

Most of these IVAs need power, and some of them also need other resources, like water and oxygen. This extra need in resources must be accounted for to size the tanks. Indeed, for example, the oxygen consumption of a group of 30 mice can use as much oxygen as an extra crew member (computed from [53]). Most activities, notably in biology, space science and technology-testing, do not use resources only when astronauts experiment on them, but all the time. Once again, we can take the example of mice, but also of plant growth or of the use of cameras to study space phenomena [52].

Therefore, a function was added into HabNet, representing user-input IVA-related needs and outputs. Based on the experiments led on the ISS, described in [52], it was decided that the IVA would need and generate resources all the time.

5.4 Adding margins for sizing

When sizing a habitat for a given mission, it is necessary to account for disruptions. Such disruptions include having to extend the mission by a few days, or needing extra resources to carry out an unplanned mission. In order to account for these potential disruptions, a margin, measured in days of mission, was added to the mission duration input by the user. These extra days of mission are run for emergency purposes. Under such emergency scenario, HabNet considers that most technologies (except vital ones) stop working, so resources are not recycled anymore. VCCR keeps operating to evacuate carbone dioxide from the habitat to avoid carbon dioxide poisoning. The astronauts keep their usual schedule, except that IVAs and EVAs are cancelled to save resources. In-Situ Resource Utilization (ISRU) is not available anymore. The amount of resources added to the habitat during sizing would allow for the crew to survive during this time margin, as long as no vital technology stops functioning.

In [54], studying a Mars Habitat, the recommended margin is a 30-days open-loop consumable backup. For Moon habitats, in [55], power systems are sized for 16 days backup. Since this research experiments aim to simulate a Moon habitat, the margin selected for the experiments is 16 days (384 hours).

5.5 Adding technologies

To highlight the comparison capabilities of the environment developed, a few technologies were added to the existing tool. In particular, In-Situ Resource Utilization (ISRU) and solar arrays were implemented.

5.5.1 ISRU: water and oxygen extraction

In-Situ Resource Utilization refers to technologies the enable the extraction of resources from the environment of the habitat. On the Moon, oxygen is present within lunar regolith and water, as ice, is also available at the poles of the celestial body [12, 48]. On the red planet, both the atmosphere (containing CO_2) and the soil (containing water) can be processed to collect oxygen [56, 57].

Following the same logic than as the one implemented for other technologies, a function was embedded into HabNet to consider the power needed for ISRU. Such consideration was not included previously. Since this research focuses mostly on lunar habitats, ISRU processes to harvest water on the Moon were studied. In particular, Planetary Volatiles Extractor (PVEx) technologies were investigated. PVEx are able to extract volatiles (such as ice) trapped in regolith by heating them while drilling the ground [47]. Since most of ISRU research is focused on Mars missions, the power needs and weight of a system converting ISRU-extracted water to O_2 were estimated from research for Mars ISRU [57]. The energy needed for in-situ resource extraction and transformation can be found in Table 5.1. The mass needed for these technologies was also estimated from Mars technologies because little information was available.

Table 5.1: Energy needs for water and oxygen ISRU, per kg of resource produced, from [47, 57]

Resource	Energy needs [kWh]
Water	2.2
Oxygen	9.62

5.5.2 Power generation

Two of the most widely considered technologies for power generation on the Moon are solar arrays and nuclear (fission) power [48, 58]. A nuclear power source with a 500 kW_e

capacity was already implemented in HabNet. Modifications have been made by the author so that the capacity of the nuclear power generation system now depends on the sizing process. To estimate the mass and power needed for such a facility, it is assumed to use Brayton dynamic power production to match studies in [48].

A simplified solar power production model was also implemented to add subsystem alternatives for demonstration purposes. It computes the power produced by solar arrays assuming an average constant light along the lunar day. To do so, lunar diurnal insolations were extracted from [59], as shown in Table 5.2.

Seleno-graphic latitude	**Hori-zontal**	**S 30**	**S 45**	**S 60**	**S 90**	**N 30**	**N 45**	**N 60**	**E 30**	**E 45**	**E 60**	**E 90**
0°	1107	958.7	782.8	553.5	0	958.7	782.8	553.5	1032.9	944.9	830.3	553.6
10°	1090.2	1040.2	906.8	711.6	192.2	848.0	634.9	378.6	1019.3	934.8	824.0	553.6
20°	1040.2	1090.2	1003.3	848.0	378.6	711.6	467.8	192.2	979.1	904.9	805.5	553.6
30°	958.	1107.0	1069.3	958.7	553.5	553.5	286.5	0	914.1	856.7	775.6	553.6
40°	848.0	1090.2	1102.8	1040.2	711.6	378.6	96.5	0	827.0	792.9	736.2	553.6
50°	711.6	1040.2	1102.8	1090.2	848.0	192.2	0	0	722.3	716.9	689.2	553.6
60°	553.5	958.7	1069.3	1107.0	958.7	0	0	0	605.8	633.3	637.3	553.6
70°	378.6	848.0	1003.3	1090.2	1040.2	0	0	0	485.6	547.5	583.3	553.6
80°	192.2	711.6	906.8	1040.2	1090.2	0	0	0	372.3	465.2	529.9	553.6

Table 5.2: Lunar diurnal insolations [MJ/m^2] depending on the orientation of the surfaces, from [59]

The best case for each latitude is highlighted in yellow. The average power received by solar arrays during an hour at a given latitude was calculated from these values, using a linear interpolation, when necessary. With the latitude, the yield and the surface of the solar arrays, the power produced by the solar arrays can be computed using [59]:

$$P_{produced} = P_{received}(latitude) \cdot yield \cdot surface \tag{5.1}$$

Once all these changes are implemented, the tool is ready to be used in the context of the methodology developed during this research. The first step consists in establishing criteria to compare the new elements implemented in the tool (partial activation rates, new technologies).

5.6 Establishing value

ESM (Equivalent System Mass) is the standard criterion used by most researchers to evaluate the performance of space subsystems [34]. In particular, it is used by the existing sizing and simulation tools for space habitat subsystems to compare different technological alternatives [32, 35]. A developed equation for ESM can be found in [34]:

$$\begin{aligned} ESM = \sum_{i=1}^{n} [& M_{I_i} \cdot SF_{I_i} + V_{I_i} \cdot V_{eq_i} + P_i \cdot P_{eq_i} + C_i \cdot C_{eq_i} + CT_i \cdot D \cdot CT_{eq_i} \\ & + M_{TD_i} \cdot D \cdot SF_{TD_i} + V_{TD_i} \cdot D \cdot V_{eq_i}] \end{aligned} \tag{5.2}$$

where ESM is the equivalent system mass of the system considered, in kg,
M_{I_i} is the initial mass of the subsystem i, in kg, and SF_{I_i} is the initial mass stowage factor for the subsystem i, in kg/kg of resource,
V_{I_i} is the initial volume of the subsystem i, in m^3, and V_{eq_i} is the mass equivalency factor for the pressurized volume support infrastructure of subsystem i, in kg/m^3,
the subscript TD refers to time-dependent mass and volume of the subsystem,
P_i is the power requirement of said subsystem, in kW_e, and P_{eq_i} is the mass equivalency factor for the power generation supporting subsystem i, in kg/kW_e,

C_i is the cooling requirement of subsystem i, in kW_{th}, and C_{eq_i} is the mass equivalency for the cooling of subsystem i, in kg/kW_{th},

CT_i is the crewtime requirement of subsystem i, in CM-h/y, D is the duration of the segment considered, in years, and CT_{eq_i} is the mass equivalency factor for the crewtime of subsystem i, in kg/CM-h.

For this research, ESM is calculated for comparison purposes. Therefore, the only subsystems considered are the ones that can vary from one architecture to another. Other equipment, like furniture and IVA material, is not considered.

In this research, the heat exchanges and heat systems of the habitat are not studied. Therefore, the cooling requirements or penalties are not evaluated for the alternatives investigated. No reliable data concerning the crewtime requirements was available, so the equivalent mass due to crewtime requirement is not computed either. During the mission, there are no events that would create more mass or more volume. The elements subscripted with TD can be ignored.

In order to get a more accurate evaluation of ESM for the habitat considered, it was decided to use the mass of the tanks computed during sizing instead of a mass stowage factor. Thus, for ESM computations, tanks and energy storage are considered as subsystems by themselves. Their volume and their mass after sizing are evaluated and added to the habitat's total ESM. Since the subsystems generating power are also sized, we can evaluate the needs in power for the whole system and compute their ESM accordingly. Consequently, for the subsystems assessed, the ESM equation used is simplified:

$$ESM = \sum_{i=1}^{n}[M_{I_i} + V_{I_i} \cdot V_{eq_i}] \tag{5.3}$$

In Section 5.2, Activation Rates were introduced because they can potentially reduce the mass of the system considered. Indeed, if a lower Activation Rate is used, it means that the maximum capacity of the subsystem is cut down. Therefore, the system can be downsized and its mass lowered. For the three subsystems for which an Activation Rate was created in HabNet (OGA, VCCR and WPA/UPA), an estimation of the fixed and variable mass was made based on data extracted from [26]. Each element of these subsystems was categorized as variable (if they can be downsized for a lower Activation Rate) or fixed (for sensors or valves, for example). These numbers are a rough estimation and are used for demonstration purposes only. They can be found in Table 5.3. This estimation, even if it is rough, shows that there can be some advantage to downsizing these technologies if it is possible, as the elements with variable mass and volume account for 50 to 90% of the total mass/volume.

The same kind of method can be used for ISRU. However, there is much less information

Table 5.3: Variable mass and volume for selected technologies, based on data from [26]

	OGA	VCCR	WPA/UPA
Fixed mass [kg]	51.43	45.68	115.30
Variable mass [kg]	394.36	110.64	956.70
% variable mass	88.42 %	70.78 %	89.24 %
Fixed volume [m^3]	0.087	0.186	0.189
Variable volume [m^3]	0.358	0.233	1.421
% variable volume	80.45 %	55.61 %	88.26%

available as ISRU technologies are still very much under development [56]. Therefore, for this study, we assume that the mass of ISRU is completely dependent on the amount of resources produced (100 % variable). Research was conducted to determine the mass and volume of each of the subsystems considered. The values used during this research can be found in Table 5.4. For the technologies cited in Table 5.3, the fixed mass is added to the variable mass displayed in the table, except for a 0% Activation Rate, which means that the technology does not need to be installed.

Based on [48], the mass of pressurized volume for a shielded inflatable module on the surface of the Moon would be 133.1 kg/m^3, therefore this number will be used to evaluate ESM. We consider that nuclear and solar facilities do not need pressurized volume in the module. During this study, the EMU technologies will be considered to have the same weight and volume. They will be compared based on other criteria: TRL, maintainability and safety.

These criteria can be used to compare various feasible configurations, which must be sized beforehand so their value (ESM, readiness level, safety, maintainability, in this research) can be evaluated. Chapter 6 focuses on the single and multi-mission sizing methods developed in this thesis.

Table 5.4: Masses and volumes considered for ESM calculations

Subsystem	Unit	Mass [kg/unit]	Pressurized volume [m^3/unit]
Oxygen tanks	kg of O_2	1.364 [48]	$8.76 \cdot 10^{-3}$ (liquid)
Water tanks	kg of water	1.200 [60]	10^{-3} for sea-level pressure and temperature
Nitrogen tanks	kg of N_2	1.524 [48]	$5.22 \cdot 10^{-3}$ at 2,500 psia [61]
Batteries (Li-ion)	Wh	0.025 [48]	$2 \cdot 10^{-5}$ [48]
Dry waste tanks	kg of dry waste	1	$3.56 \cdot 10^{-3}$ [62]
OGA	%	3.94	0.0036
VCCR	%	1.95	0.0023
WPA/UPA	%	9.57	0.0142
Nuclear power	kW_e	between 29 and 76 [48]	0
Solar power	kW_e	54 [48]	0
ISRU water extraction	L/hr	>144 [47]	0
ISRU oxygen extraction	kg/hr	385.88 [47, 57]	0

CHAPTER 6
GENERATE ALTERNATIVES

This section describes the steps undertaken to size multi-mission alternatives for space habitat subsystems. A roadmap of the steps taken to achieve this objective is displayed in Figure 6.1. This implementation also allowed to test **Hypothesis 1.1**,**Hypothesis 1.2.1** and **Hypothesis 1.2**.

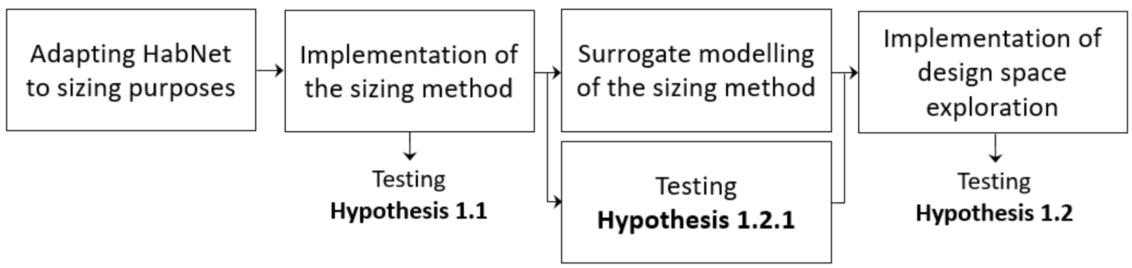

Figure 6.1: Steps taken to test **Hypotheses 1.1, 1.2.1 and 1.2**

6.1 Implementation of an open-loop sizing methodology

In this section, we will focus on the process leading to the implementation of the sizing tool. In order to verify the results of the sizing method, the sized habitats were run in HabNet, which is the only validated simulation tool for space habitat subsystems and the basis of the tool developed. This step is also meant to test **Hypothesis 1.1** by comparing the capabilities of existing tools with the new tool developed.

The methodology selected to size the habitat subsystems is based on the open-loop method used in ELISSA [35] and described in Figure 4.2. This process allows to size the resource tanks, based on the following process:

- First, the tanks are oversized for the input mission, using blank runs and values found in the literature

- Then, the mission is run in HabNet, adding an adequate margin. At this point, the tanks and the power generators are resized based on the amount of resources consumed during the mission

- Finally, the mission is run again in HabNet to check that no failures or problems occur along the mission

This method focuses on sizing resource tanks. The inputs and outputs of the sizing method are described in Table 6.1.

Table 6.1: Inputs and outputs of the sizing tool

Inputs	Outputs
Mission Duration	Reason of death (0-6)
Number of Crew	Size of O_2 tank
Number EVA/week	Size of N_2 tank
Length of EVA	Size of water tank
ISRU production (2)	Battery capacity
IVA inputs/outputs (9)	Size of dry waste tank
EMU technologies (2)	Size of power generator
Power generation technology	
Activation rate (3)	

During space missions, nitrogen is used mostly for cooling purposes [61]. The cooling system is not implemented in HabNet, therefore the N_2 tank size only accounts for air leaks in the habitat.

6.1.1 Oversizing the tanks

In order to follow the methodology described in Chapter 4, it is necessary to oversize the tanks for the mission described. The values listed by NASA for human needs [26] were used as references to estimate the size of the tanks necessary to a given mission and get an order of magnitude for the amount of resources needed to accomplish said mission. These numbers can be found in Table 6.2. They are added to the IVA needs in resources to pre-size the tanks.

Table 6.2: List of human needs for resources, per crew member per day, from NASA [26, 48], and numbers selected to oversize the tanks in HabNet

Resource	Human needs [48]	Initial tank size
Oxygen (kg)	0.816	0.96
Potable water (L)	2.5	12
Food (MJ)	12.59	20.93
Dry waste	0.109	0.15

We can note that the initial size for water tanks is larger than expected: it was increased after several mission failures due to dehydration of the crew. In [48], the amount of water needed per crew member per day only accounts for consumed water (food and drink), which is not the case in HabNet, where other needs, related to hygiene, are also considered.

Then, HabNet was run for various missions to check that no resources were missing and that the tanks and power generator were indeed oversized.

6.1.2 Running the mission in HabNet

Once the tanks are oversized, the mission is run in HabNet, taking the extra 16-days margin into account. The tanks are then resized to match the maximum amount of resources consumed during the simulation:

$$New\ size = Initial\ size\ of\ tank\ - Minimum\ amount\ of\ resources\ in\ tank$$

The power generator is sized based on the maximum amount of energy withdrawn by the system during the mission. This helps ensure that the tanks and the power generator are sized for the needs of the mission.

A few runs showed that the amount of power that the power generation must be able to provide for the system is equal to the size of the power storage. This is due to the fact that the power generator is sized based on the maximum amount of power needed by the power storage, which is sized based on the maximum amount of energy needed by the habitat during one hour. These two quantities are equal to each other because the habitat extracts power from the power storage for its various needs and the power storage then needs this exact quantity from the power generator. These two numbers would be different if the power generation facility was shut down during the emergency phase described in Section **??**.

6.1.3 Final check for failures

To check that the amount of resources carried for the mission is sufficient, HabNet is run a second time. If the simulation is a failure, which means that crew members had a probability of dying larger than 10^{-6} due to a lack of resources, then the sizing process failed.

For the purpose of this thesis, the sizing methodology has been run several thousand times and the second run of the simulation tool has always been a success. These successes verify the sizing method. However, there is no data accessible to validate this sizing process. HabNet is the only space habitat simulation tool that was validated using actual data downstreamed from the ISS [1]. Therefore, verifying that the sizing method logically sizes habitats for HabNet is the closest we can get to validation.

6.1.4 Results for the lunar mission

Using the sizing process for the two lunar missions presented in Chapter 4, Table 4.3, we obtain the results displayed in Table 6.3.

Even if the two missions sized seem quite similar, there is a huge difference between the size of the oxygen tanks. This is due to the amount of oxygen consumed by IVAs in Mission 1. Indeed, for both missions, in-situ oxygen extraction is implemented, allowing to recover up to 0.5 moles/hour. For Mission 2, this allows to recover slowly from the oxygen consumed during EVAs. However, for Mission 1, IVAs consume exactly the amount of oxygen extracted; therefore, the oxygen necessary for all the mission's EVAs must be stored.

In HabNet, the nitrogen is only used as an atmosphere component. The size of the nitrogen tanks mostly accounts for leaks in the habitat, which are assumed to be constant in this case. Therefore, the size of the nitrogen tanks is almost linear in the mission duration.

The size of the water tanks is mostly dependent on the margin implemented for the mission. When recycled correctly, the amount of water needed for the mission is very low and depends mostly on the threshold at which the water recycling technologies start working.

The size of the power storage is very low using this sizing methodology. There are two main reasons for this: first, the power generation system is sized based on the needs of the habitat. Therefore, the power storage is used only to store the power needed by the habitat during one hour. The second reason is that during the margin implemented in HabNet to account for disruptions, the power generation system is assumed to be working. If it was not the case, the size of the power tanks would increase tremendously (up to 3,757 kWh for Mission 1 and 4,075 kWh for Mission 2) to support the habitat during 16 days without generating energy.

Finally, dry waste is mainly produced by astronauts and urine recycling. When urine is recycled, brine (which is not recyclable) is sent to the dry waste tanks.

The sizing process being verified, it now needs to be compared to the existing sizing processes enabled by ALSSAT [32] or ELISSA [35].

Table 6.3: Sized elements for two lunar missions

Characteristics	Mission 1	Mission 2
Mission duration (days)	210	150
Number of crew	4	6
Number EVA/week	2	2
Length of EVA (hr)	8	8
IVA	input oxygen: 0.5 mole/hr input water: 0.05 L/hr input power: 100 W/hr output oxygen: 0 mole/hr output water: 0 L/hr output power: 0 W/hr output CO_2: 0.4 mole/hr output grey water: 0.01 L/hr output dirty water: 0.04 L/hr	input oxygen: 0 mole/hr input water: 0.02 L/hr input power: 300 W/hr output oxygen: 0 mole/hr output water: 0 L/hr output power: 0 W/hr output CO_2: 0 mole/hr output grey water: 0.02 L/hr output dirty water: 0 :/hr
ISRU production	water : 0 L/hr oxygen : 0 moles/hr	

Technologies (for sizing)	Activation rate OGA: 0.4 Activation rate VCCR: 1 Activation rate WPA/UPA: 0.4 EMU CO_2 removal technology: RCA (Rapid Cycle Amine) EMU Urine management technology: MAG (Maximum Absorbency Garment) Power source: Solar	
Sized elements		
Oxygen tanks (moles)	4,587.23	1,710.89
Nitrogen tanks (moles)	339.92	221.20
Water tanks (L)	554.86	827.60
Power storage (Wh)	6,874	7,165
Dry waste	336.07	297.52

6.1.5 Advantages and drawbacks of the new sizing process

This new sizing method for space habitat subsystems was implemented to address a lack of dynamic tool to size different alternatives quickly enough to facilitate their comparison.

In order to validate **Hypothesis 1.1:** *If a medium-fidelity dynamic sizing tool for space habitat subsystems is developed, then space habitat subsystems can be sized faster than with state of the art tools*, we can compare the running times of ELISSA, the only existing dynamic sizing tool, and the new tool developed during this thesis. Dr. Detrell, from the Institute of Space Systems, University of Stuttgart, was kind enough to share ELISSA for this thesis purposes.

In [35], it is said that ELISSA takes several hours to run one mission. The tests conducted on the tool showed that it takes approximately 300 seconds to simulate one day. The sizing tool developed can take up to 417.2 seconds to size the tanks for a 2-year mission, which would take approximately two days and a half using ELISSA. In this example, the running time of the sizing tool is reduced by 575.

Therefore, **Hypothesis 1.1** is validated.

However, the tool developed uses an open-loop sizing process. Therefore, only the resource tanks can be sized using this methodology. Other systems, like technologies and their activation rates, could be sized using closed-loop methods. Doing so would improve the accuracy of the sizing process, because the impact of closed-loop subsystems on the tanks size is not accounted for when using an open-loop process. A closed-loop sizing methodology could be implemented in the future to improve the results of the tank sizing and size the different technologies selected.

The tool developed also presents fewer capabilities than ELISSA because HabNet includes fewer recycling technologies and other subsystems. However, these could be added to the simulation tool, similar to the other capabilities added during this thesis and described in Chapter 5.

6.2 Multi-mission sizing method

In order to test **Hypothesis 1.2:** *If a design space-investigating multi-mission sizing methodology is adapted to space habitat subsystems, then it can help sizing them for several different missions concurrently*, a design space exploration multi-mission sizing methodology was developed. To illustrate, implement and verify this methodology, a two-mission subsystems sizing tool was created. Three steps were taken to reach this objective:

- First, **Hypothesis 1.2.1:** *Space habitat storage can be sized for multiple missions by retaining the maximum size of storage obtained with single-mission sizing* was tested
- Then, surrogate models of the sizing methodology were developed
- Finally, this model was integrated to an environment created to facilitate design space investigation.

6.2.1 Multi-mission sizing for storage and power generators

In this thesis, because an open-loop sizing methodology was implemented, only the resource tanks and the power generation devices can be sized. The sizing tool developed in Section 6.1 can be used to validate **Hypothesis 1.2.1** for two missions. The equation tested during this experiment is:

$$Size_{mission\ \{1,2\}} = max(Size_{mission\ 1}, Size_{mission\ 2}) \tag{6.1}$$

To validate this process for two missions, a random sample of 100 missions was generated using Excel. These missions were grouped two by two, sized using the sizing tool developed in Section 6.1 and run again using the new sizes as shown in equation 6.1. All missions were a success, which validates equation 6.1. Therefore, equation 6.1 is valid. It can be generalized to n missions by induction:

$$Size_{mission\ \{1,...,n\}} = max(Size_{mission\ \{1,...,n-1\}}, Size_{mission\ n}) \tag{6.2}$$

Consequently, equation 3.1 is valid and **Hypothesis 1.2.1** is validated.

6.2.2 Surrogate modelling of the sizing methodology

Before trying to use **Hypothesis 1.2.1** to size the habitat for multiple missions, another method was tried. It consisted in modelling the success or failure of a mission based on the size of the tanks input by the user. The results shown were not very consistent, therefore the other method was also developed. The two methods developed can both be used to visualize the design space.

First attempt: Surrogate modelling of the success of the mission

In the case of HabNet, the simulation is complex, and even if it is a lot faster to run than the traditional method, it is not instantaneous. Therefore, to get an idea of the design space in which the mission would be a success, a very large number of runs would be required. Creating a surrogate model capable of predicting the size of the various elements of the habitat helps visualizing and investigating the design space. For this purpose, first, a Design of Experiments was created. Then, different methods were used to find the best fit for the results.

A Design of Experiments (DoE) aims to gather the most information out of a minimal number of experiments, the number of feasible experiments being limited by time. A DoE needs to explore the whole design space, described in Table 6.6, to generate accurate models. The success/failure of the mission was determined by varying 21 inputs, listed in Table 6.6. The limits of the design space were determined through a review of the literature and historical missions and by using the sizing tool developed during this thesis.

The Design of Experiments used consists in the combination of:

- A 128 Fractional Factorial cases design: Fractional Factorial experiments explore the corners of the design space
- A 872 Latin Hypercube cases design: Latin Hypercube designs are space-filling designs, they balance maximum spacing between the points and uniformity [63]
- A 2,000 Uniform cases design: Uniform designs select random points in the design space, limiting the bias that could be generated by other designs

The associated design space is defined in Table 6.6.

To create models of the success or failure of the mission based on the inputs defined in Table 6.6, several classification methods were used using Python and its machine learning library *sklearn* [64]. These methods and the measures of goodness used are described in Appendix B. The results obtained can be found in Table 6.5.

Table 6.5: Precision and accuracy of the success/failure models for different classification models

Classification model	Accuracy	Precision	TP	TN	FP	FN
Random Forest Classifier	0.9071	0.9175	189	612	27	55
Logistic Regression	0.8279	0.7421	141	590	49	103
Support Vector Classification	0.8403	0.7562	152	590	49	92
Gradient Boosting Classifier	0.9151	0.9338	201	607	32	43

More than 8% of the outputs of the model are wrong. Therefore, it was decided to try to use another method, using **Hypothesis 1.2.1** as described before.

Table 6.6: Bounds of the design space

Inputs (unit)	Lower bound	Higher bound	Justification
Mission Duration (hrs)	730	18,000	Between a month and 2 years
Number of crew members	2	8	Higher bound due to technology limits (VCCR)
# EVA/week	1	5	Keep 2 days per week to rest [26]
Length of EVA (hrs)	2	12	More than 12 hours: need accommodations to sleep
IVA input oxygen (moles)	0	2	Computed from ISS experiments [52]
IVA input water (L)	0	0.1	Computed from ISS experiments [52]
IVA input power (W)	0	500	Computed from ISS experiments [52]
IVA output oxygen (moles)	0	2	Computed from ISS experiments [52]
IVA output water (L)	0	0.1	Computed from ISS experiments [52]
IVA output power (W)	0	500	Computed from ISS experiments [52]
IVA output CO_2 (moles)	0	2	Computed from ISS experiments [52]
IVA output grey water (L)	0	0.1	Computed from ISS experiments [52]
IVA output dirty water (L)	0	0.1	Computed from ISS experiments [52]
ISRU water production (L)	0	2	[56]
ISRU O_2 production (moles)	0	2	[56]

EMU CO_2 removal	-	-	RCA/METOX
EMU Urine management	-	-	UCTA/MAG
Power source	-	-	Nuclear/Solar/None
Activation rates (OGA, VCCR, WPA/UPA)	0	1	
O_2 tank size (moles)	0	170,000	Maximum value obtained for 3,000 runs of sizing method
N_2 tank size (moles)	0	1,800	Maximum value obtained for 3,000 runs of sizing method
Water tank size (L)	0	25,000	Maximum value obtained for 3,000 runs of sizing method
Power storage (W)	0	13,000	Maximum value obtained for 3,000 runs of sizing method
Dry waste tanks (kg)	0	4,000	Maximum value obtained for 3,000 runs of sizing method
Power generation capacity (kW)	0	13	Maximum value obtained for 3,000 runs of sizing method

Second attempt: using the sizing method

A Design of Experiments was created to generate surrogate models for the sizing method, similarly to the DoE generated during the first attempt. The bounds of the DoE are the same, except that the tanks are not an input anymore.

To create accurate models of the sizing method based on the inputs described before, several regression techniques were used and implemented using the Python library *sklearn* [64], notably:

- Polynomial least squares regression models: using multivariate polynomial functions to model the outputs of the sizing method
- Kernel Ridge [64]: learns a function that is linear in the space defined by the kernel function (can be linear, but also polynomial, laplacian, sigmoid...) and the data
- Ada Boost [64]: fits several regressors on the dataset, adjusting the weights of the training data depending on the error of the current model
- Random Forest Regressor [65]: several decision trees are trained and their vote is averaged to determine the classification of the input
- Gradient Boosting Regressor [64]: random forest reducing the loss function by modifying each new tree parameters based on previous results.

These techniques were selected for several reasons. Kernel Ridge regression was selected as a first test. This model is simpler than the others, therefore it is less computationally expensive. The three following models are ensemble models: they combine several models (such as decision trees, for example) and aggregate their results to get the best model possible. Ensemble models usually perform well and produce more accurate solutions than what would be generated by a single model. Consequently, they are more computationally expensive.

Ensemble models can be tuned to get better results. For example, for Random Forests, several parameters can be varied, such as the number of estimators (number of decision trees which decision is averaged) or the tree depth. For these models, a grid search was conducted, comparing the results of each model to refine the parameters.

To determine if the models were a good fit, three criteria were used: R^2, applied on training and validation points, and the Mean Absolute Error (MAE), divided by the average value of the variable considered. R^2 measures how variability is accounted for in the model [63]. The Mean Absolute Error allows to evaluate the mean distance between the values predicted by the model and the real values. Dividing it by the average value of the variable estimated allows to evaluate the relative importance of the mean error. The models tested and retained (in bold) for the nitrogen tanks and for the power storage are displayed in Tables 6.8 and 6.9. The rest of the models selected for this research, along with their goodness scores, can be found in Appendix B.

Table 6.8: Models tested for N_2 tanks

Model tested	R^2 training	R^2 validation	MAE/Average
Kernel Ridge	0.9901	0.9895	5.0%
Ada Boost Regressor	0.9900	0.9888	5.2%
Random Forest Regressor	0.9986	0.9904	4.5%
Gradient Boosting Regressor	0.9941	0.9904	4.6%

Table 6.9: Models tested for power storage

Model tested	R^2 training	R^2 validation	MAE/Average
Kernel Ridge	0.9596	0.9583	1.6%
Ada Boost Regressor	0.9544	0.9445	2.2%
Random Forest Regressor	0.9963	0.9735	1.4%
Gradient Boosting Regressor	0.9942	0.9859	1.0%

6.2.3 Implementation of the methodology

In this section, the methodology developed to size space habitat subsystems for multiple missions is described. The method consists in two steps:

- Initial sizing using sizing tools
- Design Space Exploration, which allows for sizing constraints and other mission requirements to be taken into account.

As an illustration of the method described here, the environment developed in this thesis is described (see Figure 6.2). This environment was developed using **Hypothesis 1.2.1**, showing the size of the resource storage and power generator as in Figure 4.3.
On the left-hand side of the window, users can vary the different parameters of the mission (point 1) and select technologies (point 2). On the right-hand side, the design space is displayed so users can tune the size of the tanks and of the power generator (point 3). A table, indicating the values obtained by running the process described in **Hypothesis 1.2.1**, is also displayed (point 4).

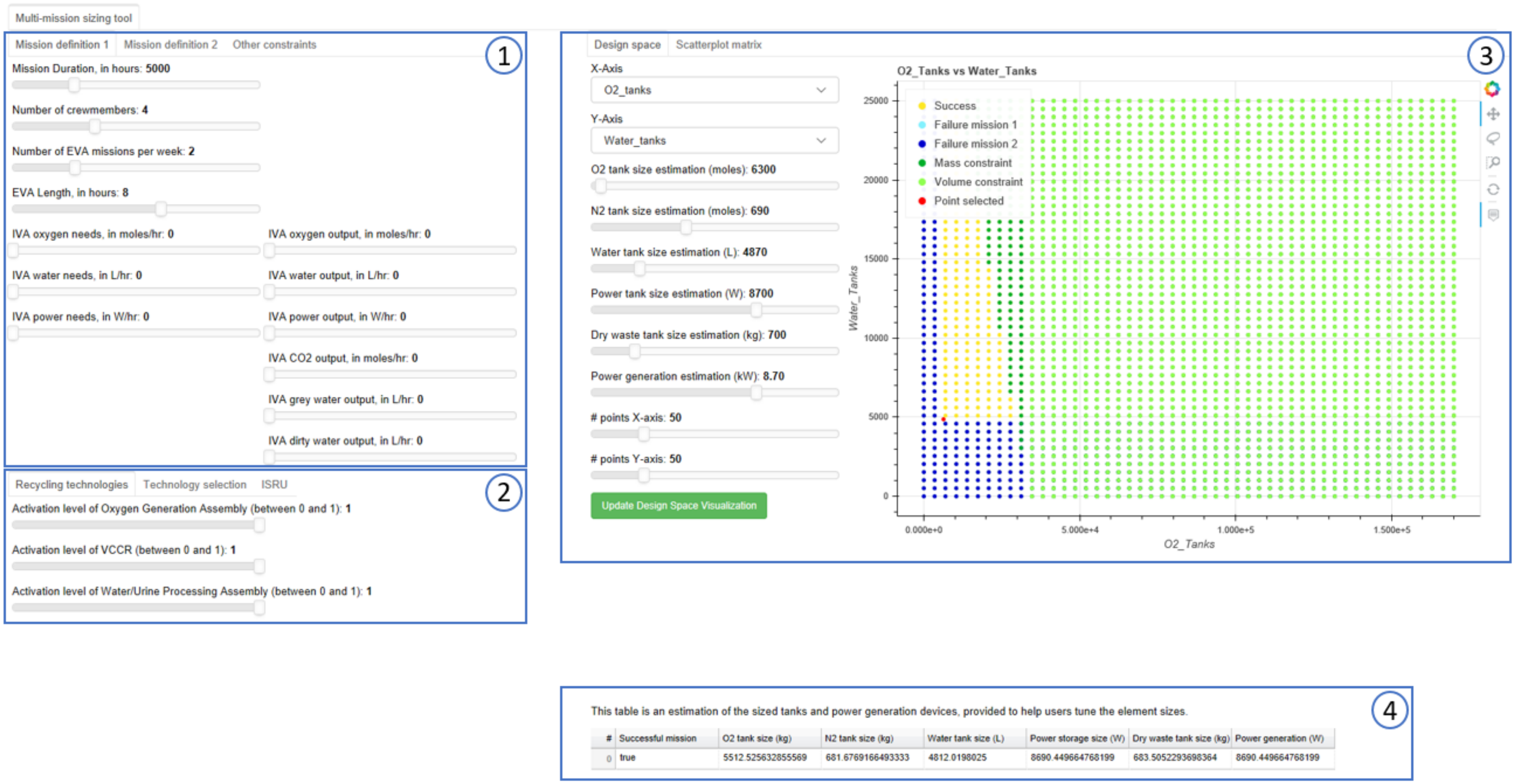

Figure 6.2: Dashboard of the tool developed for this research

6.2.4 Input the missions and technologies selected

Users first need to input the missions they want to size the habitat for. In the tool developed in this thesis, the habitat can be sized for two different missions at the same time. The technologies selected for the habitat must be input, along with their capacity or their level of activation if such a feature is available.

6.2.5 Initial sizing

To follow a design-space exploration methodology, as presented in Chapter 4, users must be able to visualize two-dimensional slices of the multi-dimensional design space. To set all other dimensions, users need to input initial tank sizes and a first estimation of the power generation needs. The open-loop sizing process developed in Section 6.1 can be leveraged to help users make an educated guess for these values.

For these elements, larger sizes do not endanger the missions, but they make them more costly, as is illustrated in the definition of ESM in Chapter 3. Therefore, for this first estimation, the largest values for the tank sizes and power generator capacity are retained. They are displayed in a table in the dashboard, as shown in Figure 6.2 (point 4).

6.2.6 Design space visualization and exploration

Using these first estimates, a 2-dimensional design space can be displayed. Users can then select a point on the Pareto frontier and vary the size of the various elements. The systems situated on the Pareto frontier are said to be Pareto-efficient; they are defined by the fact that no other sized system is better on all fronts, which is why they are the systems of interest. The Pareto frontier, in this case, can be obtained by minimizing the size of the tanks and the capacity of the power generator, because reducing the size of these elements improves the performance of the configuration [34].

This process follows the methodology described in [39], using a constraint plot like in aircraft design processes. A constraint plot highlights the feasible design space in a two-dimensional space by eliminating designs that do not meet the constraints of the mission. In aircraft design, constraints are defined by mechanical equations. Dynamically-modelled space habitat subsystems do not obey such laws; therefore, the design space must be discretized to implement constraints on the mission.

A representation of the resulting two-dimensional design space for the multi-mission lunar habitat described in Table 4.3 is displayed in Figure 6.3.

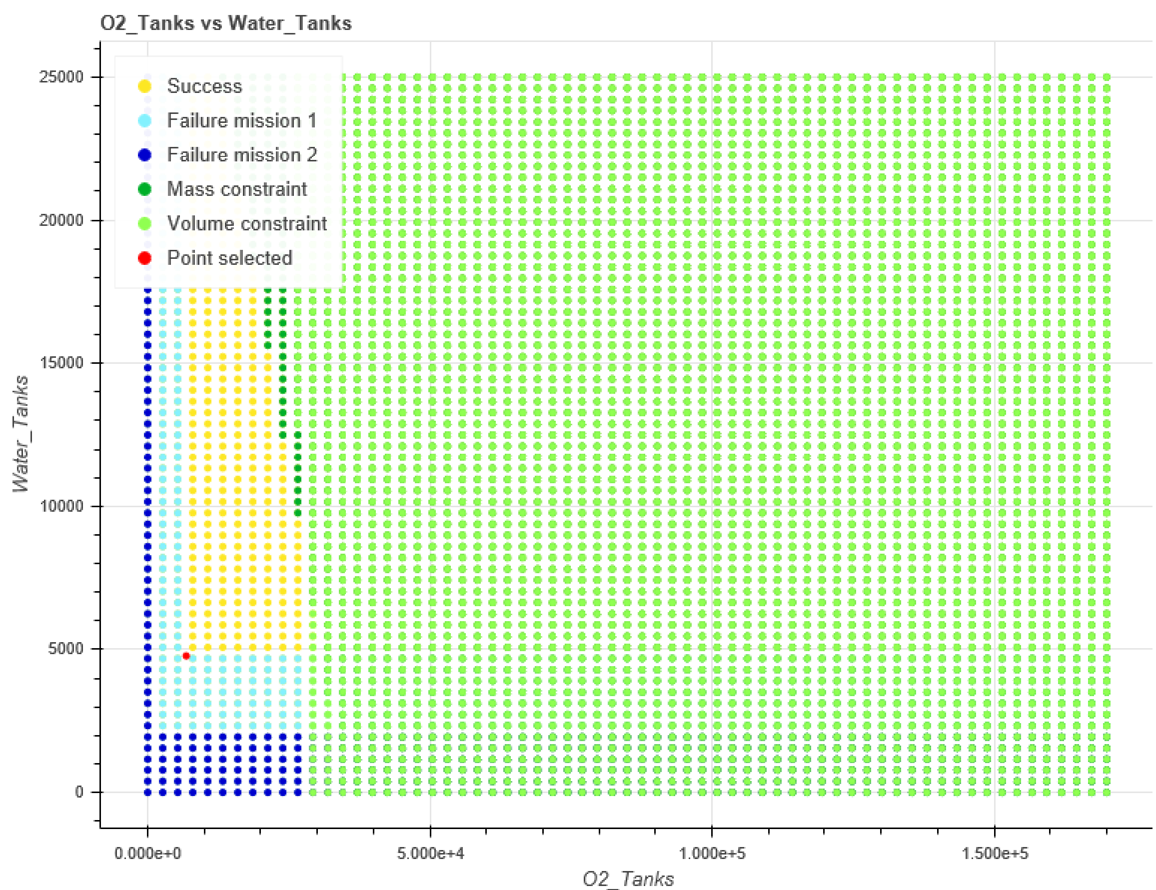

Figure 6.3: Design space exploration window

The discretization of the design space reduces the fidelity of the representation. Therefore, in this plot, the Pareto frontier is represented with an uncertainty equal to the resolution adopted for the discretization. As the design is refined, the resolution of the design space can be increased using slider bars. It is not recommended to start with a high resolution as it can greatly increase the computation time.

In the environment implemented, the users can play with two constraints: the mass of the subsystems considered and the pressurized volume these subsystems need. These constraints can be due to transportation logistics, for example. In Figure 6.3, several elements can be noticed: Mission 1 needs bigger oxygen and water tanks than Mission 2. It is more constraining because it is a longer mission that needs more resources for IVAs. However, if the two dimensions of the design space exploration window are changed, it can be shown that Mission 2 needs more power storage than Mission 1 because it uses more power during IVAs. The values obtained for the final sized habitat are displayed in Table 6.10, along with the values obtained by sizing using **Hypothesis 1.2.1**.

Table 6.10: Sized elements for two lunar missions

Element sized	After sizing	Using **Hypothesis 1.2.1**	Relative Error
Oxygen tanks (moles)	7,400	4,857	52.4%
Nitrogen tanks (moles)	350	340	2.9%
Water tanks (L)	2,200	828	165.7%
Power storage (Wh)	7,200	7,165	0.5%
Dry waste	357	337	5.9%

The second method is more accurate, because it removes all uncertainties due to surrogate modelling. However, it does not account for constraints. When simulating these two missions for the habitat sized with the tool developed, they are successful. However, the oxygen tanks and the water tanks are oversized compared to the other method, which also yields positive results.

Therefore, this visualization allows users to size the tanks and the power generator, taking into account the results from the sizing tool and other constraints. When sizing tanks and power generators, the best design is the design that respects all the constraints and has the smallest tanks.

However, all the models developed during this research are not accurate enough to permit an accurate sizing of the habitat. Several other models and possibilities were investigated, including Artificial Neural Networks (ANN). Therefore, due to the lack of precision of the models developed, **Hypothesis 1.2** cannot be validated.

CHAPTER 7

USING SET-BASED DESIGN (SBD) TO SELECT SPACE HABITAT SUBSYSTEM TECHNOLOGIES

This chapter describes the trade-off environment developed to help support design choices and test **Hypothesis 2**: *If we support design decisions using trade-off analysis, we can leverage set-based design for space habitat subsystems during the conceptual design phase.* The state-of-the-art selection process and the set-based design process developed in this thesis will then be compared.

7.1 Building the trade-off environment

The trade-off environment was built using surrogate models for the sized habitats. These models allow to evaluate the criteria described in Chapter 3, especially Equivalent System Mass (ESM), for the alternatives considered by the user.

The method followed to conduct the trade-off analysis and initiate a set-based design process is presented in Figure 7.1. In this section, the method is described step by step and illustrated by the selection of technologies for the lunar mission presented in Chapter 4, in the first column of Table 4.3.

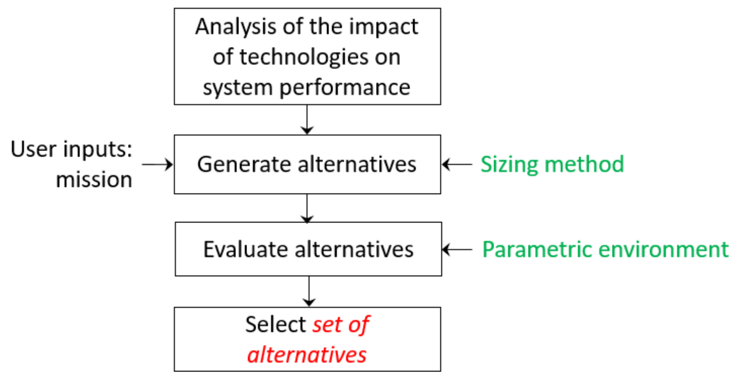

Figure 7.1: Methodology to select a first set of subsystem technologies

The surrogate models developed in Chapter 6 are leveraged to simulate the results of the sizing tool and enable the parametric and interactive visualization of trade-offs. As shown in Appendix B, these models are not able to model exactly the complexity of HabNet's outputs. This needs to be kept in mind by the users of the environment.

7.2 Step 1: Analysis of the impact of technologies on system performance

By analyzing the impact of the technologies available on the performance of the system, mainly evaluated using ESM, users can already eliminate less-performing technologies. They can also get a first overview of the trends behind the sizing process and the parameters they would need to vary to improve the performance of the system.
In the developed environment, the tools used to conduct this analysis are the Principal Component Analysis (PCA) and a scatterplot matrix.

7.2.1 Principal Components Analysis (PCA)

Principal Components Analysis enables the evaluation of the first order effects of each input variable [66]. It can be helpful if users want to get an idea of the influence of the variables on the size of the tanks and on ESM. A snapshot of the PCA is provided in Figure 7.2.

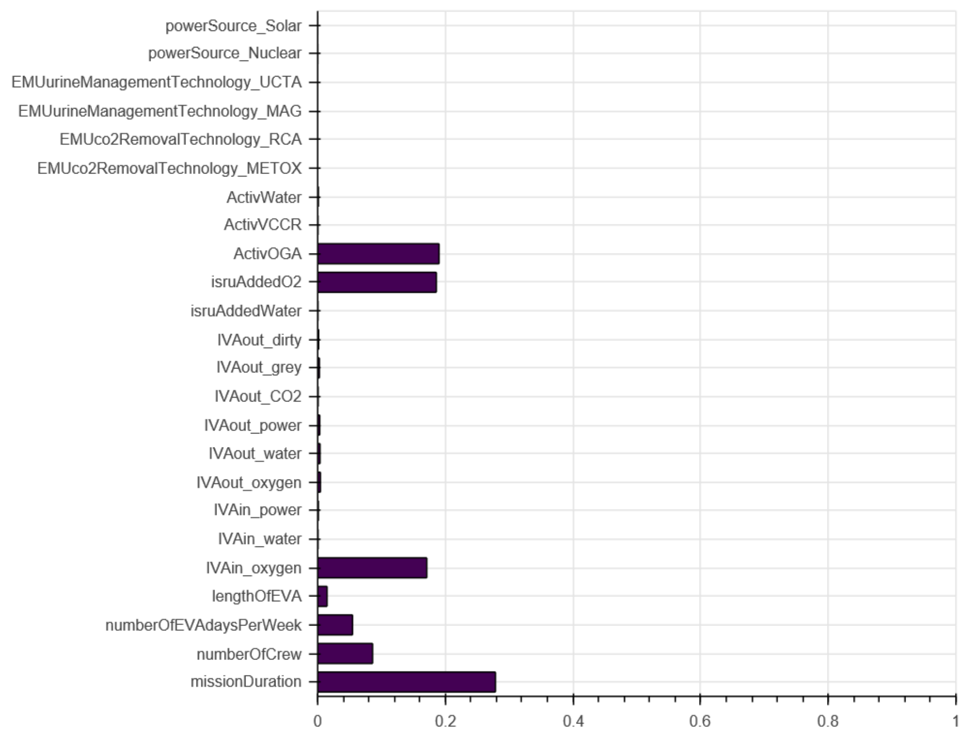

Figure 7.2: Principal Components Analysis for the size of the oxygen tanks, as displayed by the developed environment

For example, in this case, we can notice that the variables that have the most impact on the size of the oxygen tanks are linked to:

- oxygen production: through the Activation rate for the OGA, the amount of O_2 gathered from ISRU and the amount of oxygen produced during IVAs
- oxygen consumption: through the IVA needs, the number of crew and the duration of the mission

This analysis can help users understand why a mission is feasible or unfeasible. It can also highlight the importance of the various technologies evaluated: in this case, we can see that the OGA has an important impact on the size of the oxygen tanks. Indeed, the more oxygen is recycled, the less oxygen needs to be brought and stored in tanks.

7.2.2 Scatterplot matrix

A scatterplot matrix plots the sized elements against the input parameters (mission and technologies). It allows to visualize the influence of technologies on the size of each of these elements independently. A partial snapshot of the scatterplot matrix implemented in the tool can be found in Figure 7.3. It is important to note that only the successful missions are plotted in this matrix. Therefore, some of the trends, and in particular those involving the level of activation of the VCCR technology, are explained by the fact that success is conditioned by one of the parameters.

Some trends can be highlighted from this matrix. For example, as it was illustrated using the PCA, we can notice that the oxygen tanks size depends mostly on the mission duration. Other very noticeable trends appear: for example, the amount of N_2 is almost linear with the duration of the mission. This is due to the fact that in HabNet, heating and cooling are not simulated. Usually, in space missions, N_2 is mainly used to keep ammonia liquid in coldplates and heat exchangers [61]. Therefore, in this research, the need for N_2 is only due to the necessary renewal of the atmosphere due the leaks in the habitat. These leaks are considered constant throughout the mission, which explains why the amount of nitrogen necessary is linear with the length of the mission.

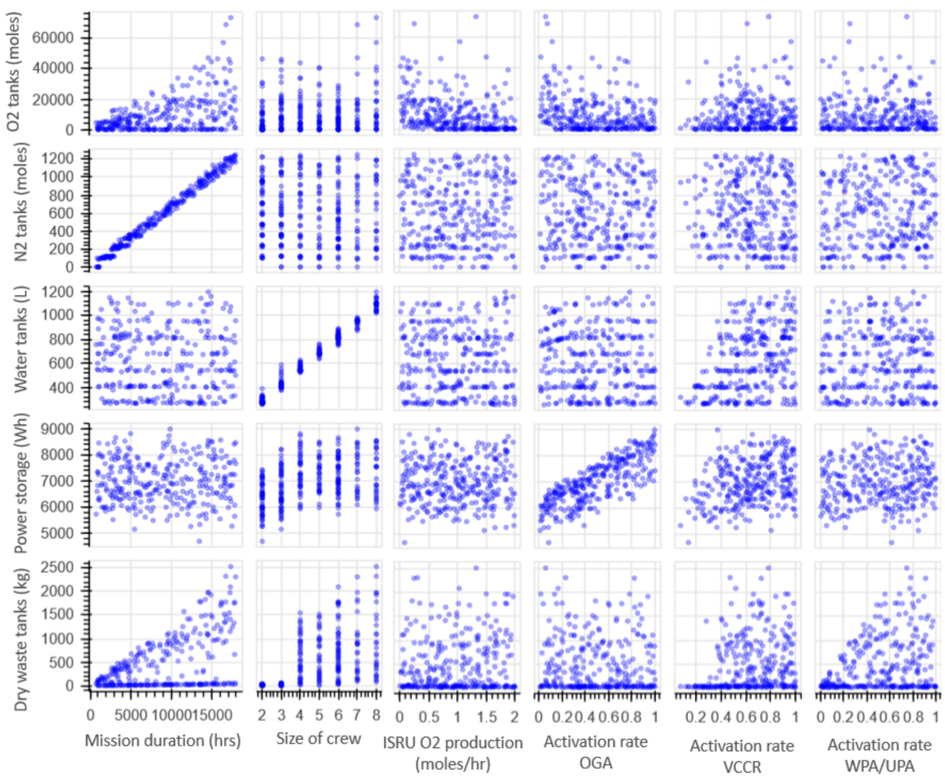

Figure 7.3: Scatterplot matrix, as displayed in the developed environment

This analysis helps users understand how to tweak parameters to improve the performance of the system. For example, the PCA and the scatterplot matrix show that trade-offs can be done between in-situ O_2 extraction, the use of the Oxygen Generation Assembly (which consumes a lot of power) and the size of the tanks. Various alternatives with different combinations of these technologies have to be compared to find the best set of alternatives, that will be brought to the next step of the design process.

7.3 Step 2: Generate alternatives

Alternatives can be generated using the technologies available and selected by the design team. These alternatives, consisting of a set of technologies with various activation levels, are then sized for the mission targeted. Then, ESM (the main criterion for space habitat performance) can be evaluated.

In the tool developed for this research, the single-mission sizing process described in Chapter 6 is leveraged to size the tanks and the power generation for the system selected.

7.4 Step 3: Compare alternatives

The sets of technologies then need to be compared using ESM, as well as other user-defined criteria that can comprise safety, maintainability and technology readiness, among others. The goal of this comparison is to eliminate less-performing solutions. Therefore, if an evaluation of the uncertainty of the mass and volume of the technologies presented is available, it should be taken into account.
In our example, used as a case study for this methodology, the technologies considered to illustrate the implementation of this methodology are:

- The activation rates of OGA, VCCR and WPA/UPA: ranging between 0 and 1, their level of activation can have an impact on the size of the element (which will have an impact on the mass of the system) and on the amount of resources that needs to be stored to accomplish the mission (which will have an impact on the size of the tanks and, therefore, on the mass of the system)

- The EMU (Extra-Vehicular Mobility Unit) CO_2 recycling technologies: RCA (Rapid Cycle Amine) and METOX (Metal-Oxide) [1]; these are assumed to have the same mass. Different TRL, levels of safety and maintainability are assumed for demonstration purposes (shown in Table 7.1)

- The EMU Urine management technologies: MAG (Maximum Absorbency Garment) does not allow to recycle urine when in EVA, whereas UCTA (Urine Collection and Transfer Assembly) does; these are assumed to have the same mass. Different TRL, levels of safety and maintainability are assumed for demonstration purposes

- The power source: solar or nuclear; their weights are different and vary depending on the amount of power necessary. TRL, safety and maintainability are also assumed to demonstrate the capabilities of the environment.

Table 7.1: Levels of technology readiness, safety and maintainability assumed for the technologies compared

Technology	TRL	Safety	Maintainability
RCA	8	9	9
METOX	9	9	7
MAG	9	9	9
UCTA	7	9	7
Solar power production	9	7	7
Nuclear power production	5	5	5

In the environment, trade-offs are facilitated by using two main tools: Design Space Exploration and TOPSIS, a Multi-Criteria Decision Making method.

7.4.1 Design Space Exploration

Design Space Exploration can also be used to compare alternatives. By mapping out these alternatives depending on the value of the criteria selected for the analysis, we can visualize the Pareto frontier. If an alternative is dominated (if it is not on the Pareto front), then it is proven to be less-performing than others: it can be eliminated. However, to be eliminated rigorously, it must be shown that the alternative is dominated in all the dimensions considered, that is to say for all criteria considered in the problem. The tool developed for design space exploration in the trade-off environment is represented in Figure 7.4. The Pareto front for the two dimensions represented is highlighted in green.

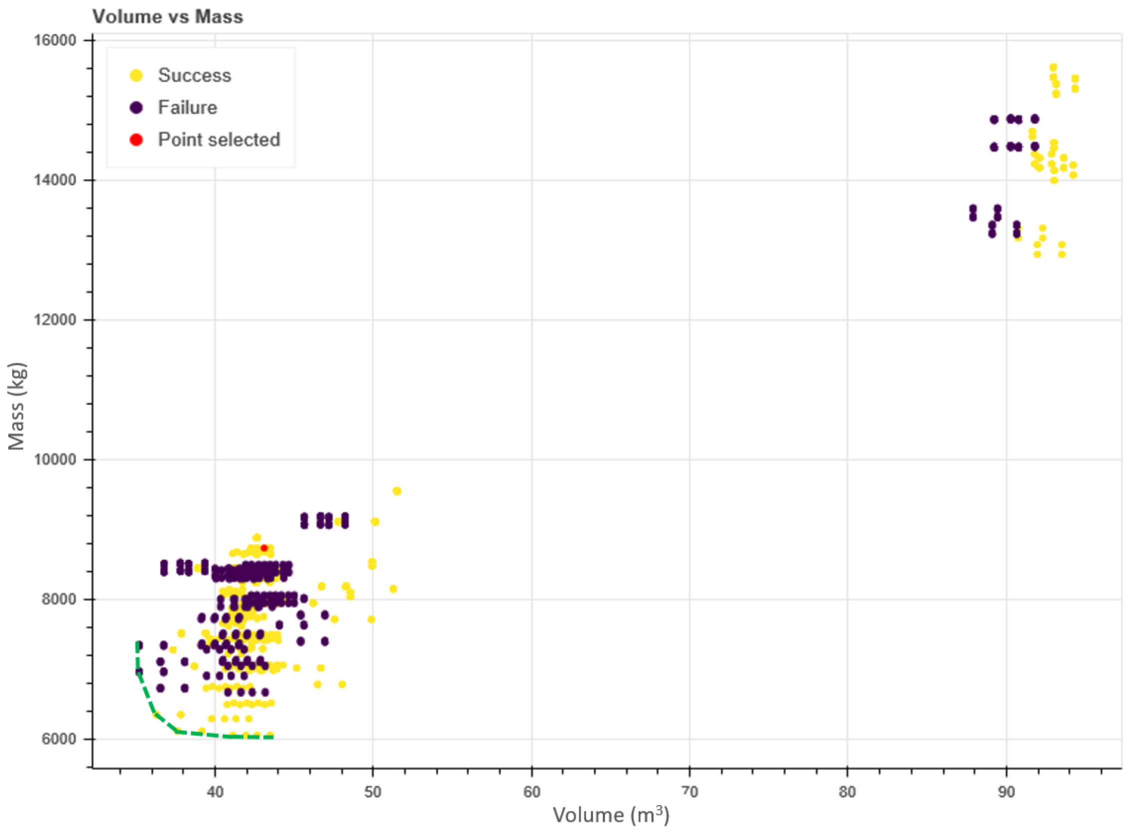

Figure 7.4: Design Space Exploration, Volume (m^3) vs Mass (kg)

In this figure, we can see that we can already eliminate a set of alternatives, the ones needing a much higher mass and volume than others. This bulk of alternatives comprises all the configurations in which the OGA is not activated, because in these cases the tanks of oxygen needed to accomplish the mission greatly increase the mass and volume of the habitat.

We can also eliminate failed missions (missions fail when the VCCR is not correctly sized and astronauts die from CO_2 poisoning). The remaining alternatives form a first set of solutions that can be refined using multi-criteria decision methods like TOPSIS.

7.4.2 Multi-criteria decision making: TOPSIS

TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) [67] is a multi-criteria decision technique ranking alternatives based on their distance to the best and worst ideal solutions. The best solution is the closest to the ideal solution and farthest to the negative ideal solution ("worst" solution). TOPSIS was selected for this analysis because it is a consistent, repeatable method. Users can change the importance of the criteria by varying their associated weights.

The table ranks a sample of cases with different technologies and activation rates. Users can then select the sets of technologies that are the most performing for their own set of criteria. The weights for the different criteria offered can be changed using slider bars. To get more consistent results and reduce the bias due to the user's own evaluation of the importance of mass, safety, maintainability and technology readiness, several TOPSIS tables can be generated and their results can be compared. Alternatives that never make it to the top of the list because they have low scores can be eliminated. To exclude an alternative from the rest of the study, when available, uncertainties can be taken into account.

The OGA activation rate, VCCR activation rate and the WPA/UPA activation rate are continuous parameters. To classify a finite number of parameters, these rates are sampled between 0 and 1, with a 0.1 step. The results for our case study, assuming that the most concerning factors are ESM, driving mission feasibility, and safety, are displayed in Table 7.2.

Based on the TOPSIS analysis, for the case of the lunar habitat, a number of alternatives were eliminated. Notably, the analysis shows that a nuclear facility is not adapted to generate power for this mission. Not only is it a technology still in development, but, at that size, it is also less efficient in terms of mass per kW produced.

Table 7.2: Results of TOPSIS for the case study: best cases

Weight of (%)	ESM	TRL	Maint.	Safety	OGA Activation rate	VCCR	WPA	EMU CO_2	EMU Urine	Power source
	50	5	5	40	0.3 to 0.4	0.3	0.1 to 0.2	RCA	MAG	Solar
	40	10	10	40	0.3 to 0.4	0.3	0.1 to 0.2	RCA	MAG	Solar
	40	0	0	60	0.3 to 0.4	0.3	0.1 to 0.2	Indifferent	Indifferent	Solar
	100	0	0	0	0.3 to 0.4	0.3	0.1 to 0.2	Indifferent	Indifferent	Solar

The TOPSIS analysis also allows to get an idea of the ideal activation rate for the OGA, the VCCR and the WPA/UPA. The best activation rate for the OGA is the smallest rate at which it can produce as much oxygen as used by the crew, which, in this case, is 0.3. This relates back to Figure 5.2, that showed that for a mission slightly shorter than the one simulated here, and not using O_2 for IVA purposes, the dioxygen production saturated at a rate around 0.2. The best activation rate for VCCR is also the smallest rate at which it can extract enough CO_2 from the habitat so astronauts do not suffer from CO_2 poisoning. To actually determine the exact best rates, an optimization algorithm could be used.

Here, some groups of points clearly appear to be better than others. In this case study, there is little difference between the different EMU technologies. Therefore, all these alternatives are retained for further analysis, that can include more time-consuming, higher-fidelity simulations and, after more consideration, prototyping and testing.

This example was used as a demonstration of the capabilities of a trade-off analysis when used in the context of set-based design, for the conceptual design phase. It follows the two main principles of set-based design [45]: it considers sets of distinct alternatives concurrently and it delays convergent decision-making. It allows to eliminate alternatives that are proven to be less performing than others, keeping those that can still be, at this level of analysis, the best fit. Therefore, **Hypothesis 2:**

If we support design decisions using trade-off analysis, we can leverage set-based design for space habitat subsystems during the conceptual design phase. is validated.

To be used for set-based design, trade-off analyses must account for all criteria and requirements associated to the design [68]. In the case of space habitats, constraints can be derived from the transportation vehicle that would bring parts of the habitat in space. In particular, depending on the number and the type of vehicles launched, mass and volume constraints would probably appear.

7.5 Comparison with existing selection methods

Even if the technologies implemented in HabNet and in the other simulation tools used to implement the existing selection process are not the same and therefore the results of the two methodologies cannot be compared, the performance of the comparison tools used can still be evaluated. ALSSAT is only accessible to U.S. persons, so PreLISSA and ELISSA were the only sizing tools available for comparison purposes. PreLISSA and ELISSA are part of the same software package. PreLISSA handles comparisons and can output a first selection of two or three sets of technologies, which can then be run using ELISSA [35].

PreLISSA allows the comparison of a given number of alternatives by computing an Overall Evaluation Criterion (OEC) encompassing several weighted criteria: ESM, TRL, reliability, safety and maintainability. The results are displayed in a table and can be ranked. This method is quite similar to the TOPSIS presented in Subsection 7.4.2. The OEC used in the TOPSIS methodology presents a few advantages compared to the criterion used in PreLISSA: in particular, by basing the ideal best and ideal worst solutions on the best scores obtained by existing technologies, performance is measured relative to the best performance reached using existing technologies and not the hypothetical best, which may not be reachable.

The new tool developed to facilitate the selection process also offers other comparison means, allowing users to visualize trade-offs and to evaluate the impact of the various technologies implemented. Not only is the simulation tool used (HabNet) higher fidelity than PreLISSA and dynamic and therefore more accurate, but it also makes the selection more rigorous by reducing the impact of the weighting of the criteria on the selected alternatives, using Design Space Exploration.

CHAPTER 8
CONCLUSION AND FUTURE WORK

Space habitats will be needed in a close future to shelter astronauts in deep-space missions. As space agencies set tough objectives, such as the development of a Moon base and the sending of humans to Mars in the 2030s, research on planetary space habitats becomes more intensive. The design of these habitats, comprising their layout and their components, will help determine the feasibility and the viability of these expeditions. Therefore, the design process used in this context can have a very high impact on the cost and the date of these missions. This is why the research objective of this thesis is to *create a methodology to dynamically size space habitats subsystems and select technologies for multiple missions*.

In this research, we highlighted several gaps in the existing methodology to size and select subsystem technologies. Consequently, an effort was conducted to refine the current process by testing methods to fill these gaps. This effort consisted in improving the sizing methodology, by allowing for a fast and dynamic multi-mission sizing, and introducing the use of set-based design for space habitat subsystems.

8.1 Hypotheses review

To test this new and improved methodology, several hypotheses were formulated. These hypotheses were:

Hypothesis 1.1: *If a medium-fidelity dynamic sizing tool for space habitat subsystems is developed, then space habitat subsystems can be sized faster than with state of the art tools.*

Hypothesis 1.2: *If a design space-investigating multi-mission sizing methodology is adapted to space habitat subsystems, then it can help sizing them for several different missions concurrently.*

Hypothesis 1.2.1: *Space habitat storage can be sized for multiple missions by retaining the maximum size of storage obtained with single-mission sizing.*

Hypothesis 2: *If we support design decisions using trade-off analysis, we can leverage set-based design for space habitat subsystems during the conceptual design phase.*

Through the development of a medium-fidelity dynamic sizing tool using HabNet [1], an existing analysis and simulation tool for space habitats, we were able to test **Hypothesis 1.1**. The running time of the developed tool was shown to be more than 500 times lower than the running time of the only available dynamic sizing tool, ELISSA [35]. Therefore, by lowering the level of fidelity of the analysis, we were able to size space habitat subsystems faster than with state of the art tools. **Hypothesis 1.1** was validated.

The methodology proposed in **Hypothesis 1.2.1** was validated by running 100 random cases in HabNet, all of which succeeded.

Creating surrogate models for the sizing methodology using HabNet and introducing them in a environment facilitating design space exploration, we tested **Hypothesis 1.2**. The lack of accuracy of the surrogate models developed did not allow to validate **Hypothesis 1.2**.

Finally, trade-off analyses were performed to select technologies and configurations for space habitat subsystems. These analyses permitted to eliminate some alternatives, following the principles of set-based design for the conceptual design phase. Therefore, **Hypothesis 2** was validated.

The overall methodology, as developed in this thesis, has been used to perform trade-off analyses with the technologies available for a lunar habitat and select the best set of alternatives, that would need further development in the case of a real mission.

Compared to the existing methodology, the process developed is faster and allows easier comparisons. By facilitating the comparison of large sets of alternatives, it becomes an enabler for set-based design and can even help stakeholders select which technologies they should fund to improve the state-of-the-art habitat.

8.2 Future work

The work performed in this thesis could be extended in numerous ways. First of all, the surrogate models could be improved to try to test **Hypothesis 1.2**. The simulation software, HabNet, could be enhanced to include new technologies and therefore allow for more trade-off analyses. The multi-mission design space-investigating sizing method could be automated and therefore integrated in the methodology allowing for set-based design. Uncertainties could be taken into account, in order to make the set-based design process more rigorous. The process could also easily be adapted to take disruptions into account.

8.2.1 Improving the surrogate models

As mentioned in Chapter 6.1, there is randomness embedded in HabNet for the scheduling of the EVAs. This randomness adds noise to the results of the sizing method and reduces the accuracy of the models. By removing all stochasticity from HabNet, the models generated should be improved.

Trying other modelling techniques, especially ensemble methods as they seemed to be the most accurate in this case, could also enhance the models for the sizing method.

8.2.2 Adding new technologies in HabNet

First of all, it is necessary to consider the fact that HabNet does not take heat exchanges into account. On the ISS, part of the heating and cooling was provided by circulating ammonia around the station, taking advantage of the hotter and colder surfaces of the spacecraft [61]. However, for a planetary habitat, it is likely that the complete habitat will have the same temperature. which can oscillate between -230 and 120°C [69]. Therefore, heating and cooling systems will need to be implemented on the habitat and on the power generation systems. Various technologies can be considered for this purpose, therefore it could be interesting to perform trade-off studies on the subject.

Growing food in the habitat could also help reducing ESM by decreasing the amount of food that needs to be sent for the mission. HabNet already has capabilities to simulate the growth of crops, so various configurations could be studied and compared.

Other technologies, such as the Bosch process [31], an alternative to the Oxygen Generation Assembly currently implemented in HabNet, could be implemented to help perform trade-off studies. The trade-off environment developed during this thesis could help selecting the valuable technologies under development, that could bring important advances to the state of the art.

8.2.3 Closed-loop sizing process

In this research, an open-loop sizing methodology was developed. This methodology could be improved by adding a feedback loop. In the current sizing methodology, it is not possible to size recycling technologies, because the size of the tanks impacts the size of the recycling technologies and *vice-versa*. A closed-loop method, balancing the amount of resources necessary and the capacity of the recycling technologies, could help finding a better design.

8.2.4 Automating the multi-mission design process

The multi-mission design process implemented in this thesis is very dependent on the user, as the user chooses the point that seems the best fit for the missions input based on a design space exploration. However, this same search could be performed by an algorithm optimizing a user-input Overall Evaluation Criterion that could rely on ESM, TRL, safety and other parameters. Given that the models behind the process are not explicit, various non-gradient based optimization algorithms could be used, such as Divided Rectangles or Genetic Algorithms.

If the multi-mission process is automated, surrogate models can be created and integrated into trade-off tools. Trade-off analyses could be performed and set-based design could then be leveraged for multi-mission designs.

8.2.5 Accounting for uncertainties

In HabNet, most of the values used are approximations or averages, because the level of fidelity of the tool only allows to simulate the mission hour by hour. In order to account for uncertainties, in particular in the inputs and outputs of the different technologies under development, these values could be modelled using distribution functions (uniform, triangle, Gaussian) and vary at each timestep or be constant throughout the mission. A Monte-Carlo simulation could be launched for each mission, and the worst, average and best cases could be considered in the sizing and in the technology selection.

8.2.6 Accounting for disruptions

The tool selected to size the mission is dynamic because disruptions need to be accounted for when designing for space missions. The sizing tool could be adapted to take these disruptions into account, and, with a larger number of experiments, it could be possible to model the effect of these disruptions. This could help develop contingency plans, understand where redundancy is needed and more globally, understand the impact of a disruption on the system. If integrated into a trade-off environment, it would also demonstrate which technologies react best to these disruptions and help evaluate the resilience of the various alternatives considered.

Appendices

APPENDIX A

INPUTS OF THE MODIFIED VERSION OF HABNET

Table A.1: Inputs of HabNet, as modified for sizing purposes

Variable	Unit	Description
MISSION INPUTS		
missionDuration	hours	Mission Duration
margin	hours	Extra time for which the habitat should accommodate the crew
numberOfCrew	number of persons	Number of Crew
numberOfEVAdaysPerWeek	days/week	Number of days per week during which an EVA is performed (between 0 and 7)
numberOfEVAcrew	number of persons	Number of crew sent on EVA missions, smaller than total number of crew
lengthOfEVA	hours/EVA	Length of an EVA mission
lengthOfExercise	hours/day	Length of the daily exercise session
lengthOfSleep	hours/day	Length of the daily sleeping session
IVAListin	moles, L or W/hour	List grouping the resources needed for an hour of mission, due to IVAs
IVAListout	moles, L or W/hour	List grouping the resources output during an hour of mission, due to IVAs

TECHNOLOGIES SELECTED		
isruAddedWater	L/hr	Water produced using ISRU, per hour
isruAddedO2	kg/hr	Dioxygen produced using ISRU, per hour
EMUco2RemovalTechnology		METOX or
EMUurineManagementTechnology		MAG or
Power Source		None, Solar or Nuclear
ActivOGA		Activation rate for Oxygen Generation Assembly, between 0 and 1
ActivVCCR		Activation rate for VCCR, between 0 and 1
ActivWater		Activation rate for Water and Urine Processing Assembly, between 0 and 1
SIZED TANKS, POWER GENERATION		
initialWaterLevel	L	Size of the potable water tanks, fully filled at the beginning of the mission
initialO2StoreMoles	moles	Size of the O_2 tanks, fully filled at the beginning of the mission
dirtyWaterStoreCapacity	L	Size of the dirty water tanks, empty at the beginning of the mission
greyWaterStoreCapacity	L	Size of the dirty water tanks, empty at the beginning of the mission
h2StoreCapacity	moles	Size of the dihydrogen tanks, fully filled at the beginning of the mission
initialN2StoreMoles	moles	Size of the N_2 tanks, fully filled at the beginning of the mission
powerStoreCapacity	Wh	Energy that can be stored in the power bank, full when simulation starts

dryWasteStoreCapacity	kg	Mass of dry waste that can be stored in the store, empty when simulation starts
PowerGenerationCapacity	kW	Amount of power that can be generated by the power generator
OTHERS		
CarriedFood		Type of food carried, select only one (beans, soy, wheat, tomatoes...)
StockedDaysOfFood	days	Number of days during which the crew should be able to survive eating the food in the inventory
locallyGrownFoodCapacity	kg	Capacity of the store for locally grown food, empty when simulation starts
CropWaterStock	L	Size of crop water tanks, fully filled at the beginning of the mission
LettuceGrowthArea	m^2	Area reserved for lettuce growth
EMUfeedwaterCapacity	L	Amount of water that can be transported during EVAs
EMUo2TankCapacityKg	kg	Amount of dioxygen that can be transported during EVAs

APPENDIX B

MODELS TESTED FOR SIZING METHOD

The models are based on a Design of Experiments that run 3,000 points through the sizing process. These points were all used to model the success/failure of the configuration evaluated. Among them, 1,944 were successes: these were used to create models for the sizing method. These models were generated using two Python libraries: *keras* [70] and *scikit-learn* [64].

B.1 Presentation of the models

As described in Chapter 6, the various models sampled during this study are:

- Polynomial least squares regression models
- Kernel Ridge [71]
- Random Forest Regressor [65]
- Ada Boost [64]
- Gradient Boosting Regressor [64]

For some elements, the models developed are not accurate enough to be used for sizing and selection of technologies. Therefore, other options were investigated, such as Artificial Neural Networks (ANN).

B.1.1 Polynomial least square regression

This regression generates the polynomial model that minimizes the residual sum of squares. This model relies on the independence of the input features, ensuring the singularity of a solution. There are a few ways to improve this regression: reducing the number of input features, removing those that do not have an important impact on the outputs of the sizing method; adding higher order terms, and therefore capturing more interactions between the inputs (this can lead to overfitting).

B.1.2 Kernel Ridge regression

It is a combination of two techniques aiming to reduce the error linked to least squares regression. Ridge regression allows to consider other measures of error such as MSE (Mean Square Error) by adding a penalty to the function to be minimized [71]. The kernel trick consists in transforming the data using a bijection between the input parameters space and the outputs. Kernel Ridge regression can therefore bring better results than a simple polynomial regression.

B.1.3 Random Forest Regressor

Random forests is a bagging technique that consists in training a number of Decision Trees and averaging their predictions. The Decision Trees are trained on randomly selected bootstrap samples of the training data. When designing a random forest, several parameters can be varied. In this thesis, the depth of the trees and the number of trees were varied and optimized using a grid search. A big advantage of Random Forest Regressors is that they cannot overfit [72].

B.1.4 Ada Boost

Ada Boost [73] is a boosting technique using small decision trees (with a single split). Boosting techniques are a little similar to bagging, but instead of training the decision trees on random sets, the training sets are weighted depending on how difficult it is to classify them.

B.1.5 Gradient Boosting regression

The Gradient Boosting Regressor combines the more accurate decision trees of Random Forests and the weighted selection of training sets of Ada Boost [64]. Training the decision trees more on the sets that are harder to model can improve the overall goodness of the regression. When using the Gradient Boosting regression, a grid search was performed to optimize the models based on the depth of the trees, the number of the trees and the learning rate of the regressor.

B.1.6 Artificial Neural Networks (ANN)

ANN is a deep learning method combining artificial neurons in a network. Each of these neurons encapsulates its inputs in an activation function involving a threshold and weights that are tuned as the neurons are optimized to better model the training data, as shown in Figure B.1. While trying to improve the model, users can change the structure of the network (number of layers, connections between the layers) and the activation functions used for the neurons. These elements have a big impact on the goodness of the model.

In this research, ANN were used with 3, 5 and 10 layers, using various activation functions

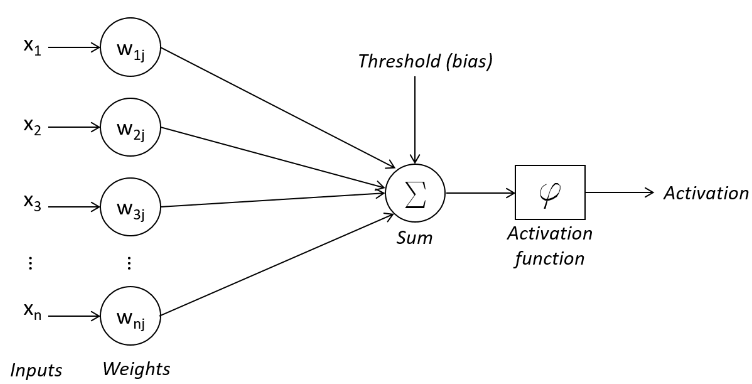

Figure B.1: Artificial neuron

such as *tanh, elu, sigmoid* or *softmax*.

B.2 Results

For each of the modelling techniques, several iterations were made and the parameters were modified depending on the performance of the results obtained. The best models generated by each method can be found in Tables B.1-9. The models selected for the study are in bold.

The main elements used to evaluate the goodness of the models are R^2, applied on training and validation points, and the Mean Absolute Error (MAE), divided by the average value of the variable considered. R^2 measures how variability is accounted for in the model [63]. The Mean Absolute Error allows to evaluate the mean distance between the values predicted by the model and the real values. Dividing it by the average value of the variable estimated allows to evaluate the relative importance of the mean error.

Table B.1: Models tested for O_2 tanks

Model tested	R^2 training	R^2 validation	MAE/Average
Polynomial (degree = 2)	0.8984	0.8599	36.5%
Kernel Ridge	0.7784	0.8234	40.3%
Ada Boost Regressor	0.6856	0.6895	53.2%
Random Forest Regressor	0.9721	0.8665	30.6%
Gradient Boosting Regressor	0.9925	0.9341	21.5%
Artificial Neural Networks	0.9042	0.8793	30.0%

Table B.2: Models tested for N_2 tanks

Model tested	R^2 training	R^2 validation	MAE/Average
Polynomial (degree = 2)	0.9921	0.9886	5.2%
Kernel Ridge	0.9901	0.9895	5.0%
Ada Boost Regressor	0.9900	0.9888	5.2%
Random Forest Regressor	0.9986	0.9904	4.5%
Gradient Boosting Regressor	0.9941	0.9904	4.6%

Table B.3: Models tested for water tanks

Model tested	R^2 training	R^2 validation	MAE/Average
Polynomial (degree = 1)	0.3191	0.2017	17.7%
Kernel Ridge	0.5295	0.4103	22.2%
Ada Boost Regressor	0.9838	0.9389	8.7%
Random Forest Regressor	0.9944	0.9944	1.5%
Gradient Boosting Regressor	0.9545	0.9472	6.9%

Table B.4: Models tested for power storage

Model tested	R^2 training	R^2 validation	MAE/Average
Polynomial (degree = 2)	0.9839	0.9724	1.5%
Kernel Ridge	0.9596	0.9583	1.6%
Ada Boost Regressor	0.9544	0.9445	2.2%
Random Forest Regressor	0.9963	0.9735	1.4%
Gradient Boosting Regressor	0.9942	0.9859	1.0%

Table B.5: Models tested for dry waste storage

Model tested	R^2 training	R^2 validation	MAE/Average
Polynomial (degree = 2)	0.9088	0.8481	23.0%
Kernel Ridge	0.8441	0.7776	42.6%
Ada Boost Regressor	0.9481	0.9427	19.5%
Random Forest Regressor	0.9983	0.9908	6.2%
Gradient Boosting Regressor	0.9996	0.9953	4.8%

Table B.6: Models tested for ESM

Model tested	R^2 training	R^2 validation	MAE/Average
Polynomial (degree = 2)	0.9023	0.8665	30.09%
Kernel Ridge	0.7170	0.6837	40.5%
Ada Boost Regressor	0.7306	0.7086	47.4%
Random Forest Regressor	0.9610	0.8502	28.1%
Gradient Boosting Regressor	0.9822	0.9217	18.7%

Table B.7: Models tested for Mass

Model tested	R^2 training	R^2 validation	MAE/Average
Polynomial (degree = 2)	0.9037	0.8692	28.4%
Kernel Ridge	0.7227	0.6825	39.2%
Ada Boost Regressor	0.7418	0.7166	45.1%
Random Forest Regressor	0.8749	0.9771	24.8%
Gradient Boosting Regressor	0.9922	0.9386	16.6%

Table B.8: Models tested for Volume

Model tested	R^2 training	R^2 validation	MAE/Average
Polynomial (degree = 2)	0.9010	0.8641	31.3%
Kernel Ridge	0.7144	0.6728	45.6%
Ada Boost Regressor	0.7145	0.7174	49.74%
Random Forest Regressor	0.9751	0.8662	28.5%
Gradient Boosting Regressor	0.9966	0.9228	20.1%

B.3 Modelling success and failure

To model the success or failure of a mission, the models used are classification models. Four models were used:

- Logistic Regression: uses the logistic function to predict a binary output
- Support Vector Classification: computes the optimal hyperplane separating successes and failures
- Random Forest Classifier: similarly to Random Forest Regressor, averages the votes of binary decision trees to make a decision
- Gradient Boosting Classifier: weights training sets depending on how difficult they are to classify, similarly to Gradient Boosting Regressor.

To determine if the models for success were a good fit, two criteria were used: the precision of the model and its accuracy. The precision of the model describes the ability of the model not to label as positive a negative sample. In the context of this research, the higher the precision, the higher the chance that a mission labelled as “successful” is, indeed, successful. If the precision of the model is low, then there is a chance that the sized habitat, selected because the mission is a success, really is a failure. The accuracy of the model describes its ability to predict correctly the outcome of the mission *i.e.* a success or a failure. The number of true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN) in the validation sample were also noted and compared. The parameters of the models were varied and monitored to try to get the best model possible. Table B.9 lists the best precision and accuracy metrics found for each classification technique.

Table B.9: Models tested for success

Classification model	Accuracy	Precision	TP	TN	FP	FN
Logistic Regression	0.884	0.9106	486	116	143	5
Support Vector Classification	0.8987	0.8922	472	204	55	14
Random Forest Classifier	0.9000	0.9107	471	204	55	20
Gradient Boosting Classifier	0.9187	0.9759	486	203	56	5

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